



US011178818B2

(12) **United States Patent**
Brammeier et al.

(10) **Patent No.:** **US 11,178,818 B2**
(45) **Date of Patent:** **Nov. 23, 2021**

(54) **HARVESTING MACHINE CONTROL SYSTEM WITH FILL LEVEL PROCESSING BASED ON YIELD DATA**

(71) Applicant: **Deere & Company**, Moline, IL (US)

(72) Inventors: **Tyler S. Brammeier**, Okawville, IL (US); **Noel W. Anderson**, Fargo, ND (US); **Benjamin M. Smith**, Falls Church, VA (US)

(73) Assignee: **Deere & Company**, Moline, IL (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 102 days.

(21) Appl. No.: **16/432,557**

(22) Filed: **Jun. 5, 2019**

(65) **Prior Publication Data**

US 2020/0128734 A1 Apr. 30, 2020

Related U.S. Application Data

(63) Continuation-in-part of application No. 16/171,978, filed on Oct. 26, 2018.

(51) **Int. Cl.**

A01D 41/127 (2006.01)

G05D 1/02 (2020.01)

(52) **U.S. Cl.**

CPC **A01D 41/127** (2013.01); **G05D 1/0212** (2013.01); **G05D 2201/0201** (2013.01)

(58) **Field of Classification Search**

CPC **A01D 41/127**; **G05D 1/0212**; **G05D 2201/0201**

(56) **References Cited**

U.S. PATENT DOCUMENTS

3,568,157 A 3/1971 Downing et al.

3,580,257 A 5/1971 Teague

(Continued)

FOREIGN PATENT DOCUMENTS

AR 108898 A1 10/2018

AU 20100224431 A1 4/2011

(Continued)

OTHER PUBLICATIONS

Lingli et al., "Characteristics Analysis and Classification of Crop Harvest Patterns by Exploiting High-Frequency MultiPolarization SAR Data," 2014, vol. 7, Publisher: IEEE.*

(Continued)

Primary Examiner — Tuan C To

(74) *Attorney, Agent, or Firm* — Christopher J.

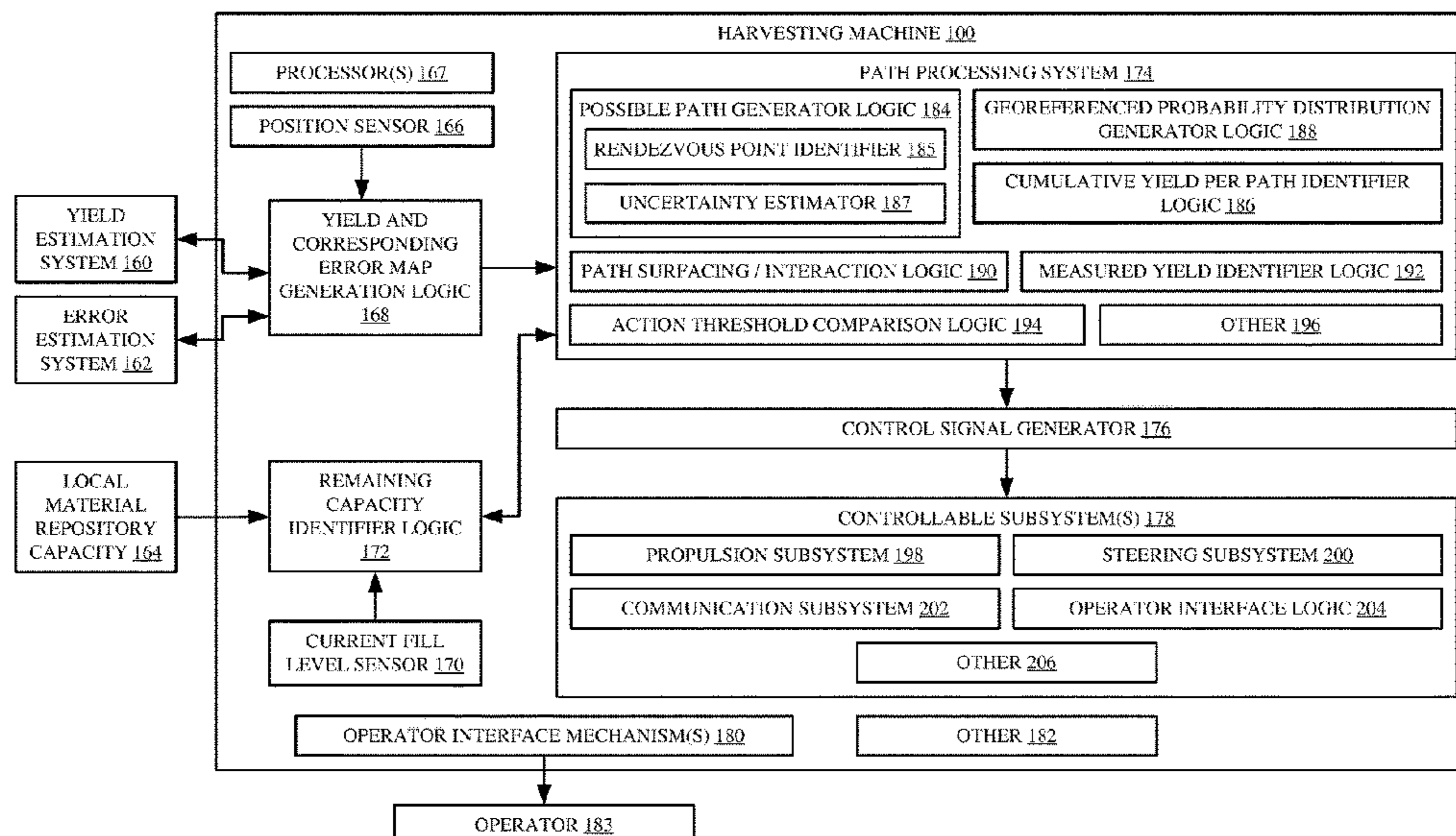
Volkman; Kelly, Holt & Christenson, PLLC

(57) **ABSTRACT**

An agricultural harvesting machine comprises a path processing system that obtains a predicted crop yield at a plurality of different field segments along a harvester path on a field, and obtains field data corresponding to one or more of the field segments generated based on sensor data as the agricultural harvesting machine is performing a crop processing operation. A yield correction factor is generated based on the received field data and the predicted crop yield at the one or more field segments. Based on applying the yield correction factor to the predicted crop yield, a georeferenced probability metric is generated indicative of a probability that the harvested crop repository will reach the fill capacity at a particular geographic location along the field. A control signal generator generates a control signal to control the agricultural harvesting machine based on the georeferenced probability metric.

(Continued)

20 Claims, 16 Drawing Sheets



(58) **Field of Classification Search**
 USPC 701/50
 See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

3,599,543 A	8/1971	Kerridge	6,236,924 B1	5/2001	Motz et al.
3,775,019 A	11/1973	Konig et al.	6,272,819 B1	8/2001	Wendte et al.
3,856,754 A	12/1974	Habermeier et al.	6,327,569 B1	12/2001	Reep
4,129,573 A	12/1978	Bellus et al.	6,374,173 B1	4/2002	Ehlbeck
4,166,735 A	9/1979	Pilgram et al.	6,380,745 B1	4/2002	Anderson et al.
4,183,742 A	1/1980	Sasse et al.	6,431,790 B1	8/2002	Anderegg et al.
4,268,679 A	5/1981	Lavanish	6,451,733 B1	9/2002	Pidskalny et al.
4,349,377 A	9/1982	Durr et al.	6,505,146 B1	1/2003	Blackmer
4,360,677 A	11/1982	Doweyko et al.	6,505,998 B1	1/2003	Bullivant
4,435,203 A	3/1984	Funaki et al.	6,539,102 B1	3/2003	Anderson et al.
4,493,726 A	1/1985	Burdeska et al.	6,549,849 B2	4/2003	Lange et al.
4,527,241 A	7/1985	Sheehan et al.	6,584,390 B2	6/2003	Beck
4,566,901 A	1/1986	Martin et al.	6,591,145 B1	7/2003	Hoskinson et al.
4,584,013 A	4/1986	Brunner	6,592,453 B2	7/2003	Coers et al.
4,687,505 A	8/1987	Sylling et al.	6,604,432 B1	8/2003	Hamblen et al.
4,857,101 A	8/1989	Musco et al.	6,682,416 B2	1/2004	Behnke et al.
4,911,751 A	3/1990	Nyffeler et al.	6,687,616 B1	2/2004	Peterson et al.
5,059,154 A	10/1991	Reyenga	6,729,189 B2	5/2004	Paakkinen
5,089,043 A	2/1992	Hayase et al.	6,735,568 B1	5/2004	Buckwalter et al.
5,246,164 A	9/1993	McCann et al.	6,834,550 B2	12/2004	Upadhyaya et al.
5,246,915 A	9/1993	Lutz et al.	6,838,564 B2	1/2005	Edmunds et al.
5,250,690 A	10/1993	Turner et al.	6,846,128 B2	1/2005	Sick
5,296,702 A	3/1994	Beck et al.	6,932,554 B2	8/2005	Isfort et al.
5,300,477 A	4/1994	Tice	6,999,877 B1	2/2006	Dyer et al.
5,416,061 A	5/1995	Hewett et al.	7,073,374 B2	7/2006	Berkman
5,477,459 A	12/1995	Clegg et al.	7,167,797 B2	1/2007	Faivre et al.
5,488,817 A	2/1996	Paquet et al.	7,167,800 B2	1/2007	Faivre et al.
5,563,112 A	10/1996	Barnes, III	7,191,062 B2	3/2007	Chi et al.
5,585,626 A	12/1996	Beck et al.	7,194,965 B2	3/2007	Hickey et al.
5,586,033 A	12/1996	Hall	7,211,994 B1	5/2007	Mergen et al.
5,592,606 A	1/1997	Myers	7,248,968 B2	7/2007	Reid
5,606,821 A	3/1997	Sadjadi et al.	7,255,016 B2	8/2007	Burton
5,666,793 A	9/1997	Bottinger	7,261,632 B2	8/2007	Pirro et al.
5,712,782 A	1/1998	Weigelt et al.	7,302,837 B2	12/2007	Wendte
5,721,679 A	2/1998	Monson	7,308,326 B2	12/2007	Maertens et al.
5,767,373 A	6/1998	Ward et al.	7,313,478 B1	12/2007	Anderson et al.
5,771,169 A	6/1998	Wendte	7,318,010 B2	1/2008	Anderson
5,789,741 A	8/1998	Kinter et al.	7,347,168 B2	3/2008	Reckels et al.
5,809,440 A	9/1998	Beck et al.	7,408,145 B2	8/2008	Holland
5,841,282 A	11/1998	Christy et al.	7,480,564 B2	1/2009	Metzler et al.
5,849,665 A	12/1998	Gut et al.	7,483,791 B2	1/2009	Anderegg et al.
5,878,821 A	3/1999	Flenker et al.	7,537,519 B2	5/2009	Huster et al.
5,899,950 A	5/1999	Milender et al.	7,557,066 B2	7/2009	Hills et al.
5,902,343 A	5/1999	Hale et al.	7,628,059 B1	12/2009	Scherbring
5,915,492 A	6/1999	Yates et al.	7,687,435 B2	3/2010	Witschel et al.
5,957,304 A	9/1999	Dawson	7,703,036 B2	4/2010	Satterfield et al.
5,974,348 A	10/1999	Rocks	7,725,233 B2	5/2010	Hendrickson et al.
5,978,723 A	11/1999	Hale et al.	7,733,416 B2	6/2010	Gal
5,991,687 A	11/1999	Hale et al.	7,753,824 B2	7/2010	Diekhans et al.
5,991,694 A	11/1999	Gudat et al.	7,756,624 B2	7/2010	Diekhans et al.
5,995,894 A	11/1999	Wendte	7,798,894 B2	9/2010	Isfort
5,995,895 A	11/1999	Watt et al.	7,827,042 B2	11/2010	Jung et al.
6,004,076 A	12/1999	Cook et al.	7,915,200 B2	3/2011	Epp et al.
6,016,713 A	1/2000	Hale	7,945,364 B2	5/2011	Schricker et al.
6,029,106 A	2/2000	Hale et al.	7,993,188 B2	8/2011	Ritter
6,041,582 A	3/2000	Tiede et al.	8,024,074 B2	9/2011	Stelford et al.
6,073,070 A	6/2000	Diekhans	8,060,283 B2	11/2011	Mott et al.
6,073,428 A	6/2000	Diekhans	8,107,681 B2	1/2012	Gaal
6,085,135 A	7/2000	Steckel	8,145,393 B2	3/2012	Foster et al.
6,119,442 A	9/2000	Hale	8,147,176 B2	4/2012	Coers et al.
6,119,531 A	9/2000	Wendte et al.	8,152,610 B2	4/2012	Harrington
6,128,574 A	10/2000	Diekhans	8,190,335 B2	5/2012	Vik et al.
6,141,614 A	10/2000	Janzen et al.	8,195,342 B2	6/2012	Anderson
6,185,990 B1	2/2001	Missotten et al.	8,195,358 B2	6/2012	Anderson
6,188,942 B1	2/2001	Corcoran et al.	8,213,964 B2	7/2012	Fitzner et al.
6,199,000 B1	3/2001	Keller et al.	8,224,500 B2	7/2012	Anderson
6,204,856 B1	3/2001	Wood et al.	8,252,723 B2	8/2012	Jakobi et al.
6,205,381 B1	3/2001	Motz et al.	8,254,351 B2	8/2012	Fitzner et al.
6,205,384 B1	3/2001	Diekhans	8,321,365 B2	11/2012	Anderson
6,216,071 B1	4/2001	Motz	8,329,717 B2	12/2012	Minn et al.
			8,332,105 B2	12/2012	Laux
			8,338,332 B1	12/2012	Hacker et al.
			8,340,862 B2	12/2012	Baumgarten et al.
			8,407,157 B2	3/2013	Anderson
			8,428,829 B2	4/2013	Brunnert et al.
			8,478,493 B2	7/2013	Anderson
			8,494,727 B2	7/2013	Green et al.
			8,527,157 B2	9/2013	Imhof et al.
			8,544,397 B2	10/2013	Bassett

(56)

References Cited

U.S. PATENT DOCUMENTS

8,577,561 B2	11/2013	Green et al.	9,681,605 B2	6/2017	Noonan et al.
8,606,454 B2	12/2013	Wang et al.	9,694,712 B2	7/2017	Healy
8,626,406 B2	1/2014	Schleicher et al.	9,696,162 B2	7/2017	Anderson
8,635,903 B2	1/2014	Oetken et al.	9,699,967 B2	7/2017	Palla et al.
8,649,940 B2	2/2014	Bonefas	9,714,856 B2	7/2017	Myers
8,656,693 B2	2/2014	Madsen et al.	9,717,178 B1	8/2017	Sauder et al.
8,662,972 B2	3/2014	Behnke et al.	9,721,181 B2	8/2017	Guan et al.
8,671,760 B2	3/2014	Wallrath et al.	9,723,790 B2	8/2017	Berry et al.
8,677,724 B2	3/2014	Chaney et al.	9,740,208 B2	8/2017	Sugumaran et al.
8,738,238 B2	5/2014	Rekow	9,767,521 B2	9/2017	Stuber et al.
8,738,244 B2	5/2014	Lenz	9,807,934 B2	11/2017	Rusciolelli et al.
8,755,976 B2	6/2014	Peters et al.	9,807,940 B2	11/2017	Roell et al.
8,781,692 B2	7/2014	Kormann	9,810,679 B2	11/2017	Kimmel
8,789,563 B2	7/2014	Wenzel	9,829,364 B2	11/2017	Wilson et al.
8,814,640 B2	8/2014	Behnke et al.	9,848,528 B2	12/2017	Werner et al.
8,843,269 B2	9/2014	Anderson et al.	9,856,609 B2	1/2018	Dehmel
8,868,304 B2	10/2014	Bonefas	9,861,040 B2	1/2018	Bonefas
8,909,389 B2	12/2014	Meyer	9,872,433 B2	1/2018	Acheson et al.
D721,740 S	1/2015	Schmaltz et al.	9,903,979 B2	2/2018	Dybro et al.
8,942,860 B2	1/2015	Morselli	9,904,963 B2	2/2018	Rupp et al.
8,962,523 B2	2/2015	Rosinger et al.	9,915,952 B2	3/2018	Dollinger et al.
9,002,591 B2	4/2015	Wang et al.	9,922,405 B2	3/2018	Sauder et al.
9,008,918 B2	4/2015	Missotten et al.	9,924,636 B2	3/2018	Lisouski et al.
9,009,087 B1	4/2015	Mewes et al.	9,928,584 B2	3/2018	Jens et al.
9,011,222 B2	4/2015	Johnson et al.	9,933,787 B2	4/2018	Story
9,014,901 B2	4/2015	Wang et al.	9,974,226 B2	5/2018	Rupp et al.
9,043,096 B2	5/2015	Zielke et al.	9,982,397 B2	5/2018	Korb et al.
9,043,129 B2	5/2015	Bonefas et al.	9,984,455 B1	5/2018	Fox et al.
9,066,465 B2	6/2015	Hendrickson et al.	9,992,931 B2	6/2018	Bonefas et al.
9,072,227 B2	7/2015	Wenzel	9,992,932 B2	6/2018	Bonefas et al.
9,095,090 B2	8/2015	Casper et al.	10,004,176 B2	6/2018	Mayerle
9,119,342 B2	9/2015	Bonefas	10,015,928 B2	7/2018	Nykamp et al.
9,127,428 B2	9/2015	Meier	10,019,018 B2	7/2018	Hulin
9,131,644 B2	9/2015	Osborne	10,019,790 B2	7/2018	Bonefas et al.
9,152,938 B2	10/2015	Lang et al.	10,025,983 B2	7/2018	Guan et al.
9,173,339 B2	11/2015	Sauder et al.	10,028,435 B2	7/2018	Anderson et al.
9,188,518 B2	11/2015	Snyder et al.	10,028,451 B2	7/2018	Rowan et al.
9,188,986 B2	11/2015	Baumann	10,034,427 B2	7/2018	Krause et al.
9,226,449 B2	1/2016	Bischoff	10,039,231 B2	8/2018	Anderson et al.
9,234,317 B2	1/2016	Chi	10,064,331 B2	9/2018	Bradley
9,235,214 B2	1/2016	Anderson	10,064,335 B2	9/2018	Byttebier et al.
9,301,447 B2	4/2016	Kormann	10,078,890 B1	9/2018	Tagestad et al.
9,301,466 B2	4/2016	Kelly	10,085,372 B2	10/2018	Noyer et al.
9,313,951 B2	4/2016	Herman et al.	10,091,925 B2	10/2018	Aharoni et al.
9,326,443 B2	5/2016	Zametzer et al.	10,126,153 B2	11/2018	Bischoff et al.
9,326,444 B2	5/2016	Bonefas	10,129,528 B2	11/2018	Bonefas et al.
9,392,746 B2	7/2016	Darr et al.	10,143,132 B2	12/2018	Inoue et al.
9,405,039 B2	8/2016	Anderson	10,152,035 B2	12/2018	Reid et al.
9,410,840 B2	8/2016	Acheson et al.	10,154,624 B2	12/2018	Guan et al.
9,439,342 B2	9/2016	Pasquier	10,165,725 B2	1/2019	Sugumaran et al.
9,457,971 B2	10/2016	Bonefas et al.	10,178,823 B2	1/2019	Kovach et al.
9,463,939 B2	10/2016	Bonefas et al.	10,183,667 B2	1/2019	Anderson et al.
9,485,905 B2	11/2016	Jung et al.	10,188,037 B2	1/2019	Bruns et al.
9,489,576 B2	11/2016	Johnson et al.	10,201,121 B1	2/2019	Wilson
9,497,898 B2	11/2016	Hennes	10,209,179 B2	2/2019	Hollstein
9,510,508 B2	12/2016	Jung	10,231,371 B2	3/2019	Dillon
9,511,633 B2	12/2016	Anderson et al.	10,254,147 B2	4/2019	Vermue et al.
9,511,958 B2	12/2016	Bonefas	10,254,765 B2	4/2019	Rekow
9,516,812 B2	12/2016	Baumgarten et al.	10,255,670 B1	4/2019	Wu et al.
9,521,805 B2	12/2016	Muench et al.	10,275,550 B2	4/2019	Lee
9,522,791 B2	12/2016	Bonefas et al.	10,295,703 B2	5/2019	Dybro et al.
9,522,792 B2	12/2016	Bonefas et al.	10,310,455 B2	6/2019	Blank et al.
9,523,180 B2	12/2016	Deines	10,314,232 B2	6/2019	Isaac et al.
9,529,364 B2	12/2016	Foster et al.	10,315,655 B2	6/2019	Blank et al.
9,532,504 B2	1/2017	Herman et al.	10,317,272 B2	6/2019	Bhavsar et al.
9,538,714 B2	1/2017	Anderson	10,351,364 B2	7/2019	Green et al.
9,563,492 B2	2/2017	Bell et al.	10,368,488 B2	8/2019	Becker et al.
9,563,848 B1	2/2017	Hunt	10,398,084 B2	9/2019	Ray et al.
9,563,852 B1	2/2017	Wiles et al.	10,408,545 B2	9/2019	Blank et al.
9,578,808 B2	2/2017	Dybro et al.	10,412,889 B2	9/2019	Palla et al.
9,629,308 B2 *	4/2017	Scholer A01D 41/1272	10,426,086 B2	10/2019	Van de Wege et al.
9,631,964 B2 *	4/2017	Gelinske G01F 1/662	10,437,243 B2	10/2019	Blank et al.
9,642,305 B2	5/2017	Nykamp et al.	10,477,756 B1	11/2019	Richt et al.
9,648,807 B2 *	5/2017	Escher A01D 41/127	10,485,178 B2	11/2019	Mayerle
9,675,008 B1	6/2017	Rusciolelli et al.	10,537,061 B2	1/2020	Farley et al.
			10,568,316 B2	2/2020	Gall et al.
			10,677,637 B1	6/2020	Von Muenster
			10,681,872 B2	6/2020	Viaene et al.
			10,703,277 B1	7/2020	Schroeder

(56)

References Cited

U.S. PATENT DOCUMENTS

10,729,067 B2	8/2020	Hammer et al.	2008/0248843 A1	10/2008	Birrell et al.
10,740,703 B2	8/2020	Story	2008/0268927 A1	10/2008	Farley et al.
10,745,868 B2	8/2020	Laugwitz et al.	2008/0269052 A1	10/2008	Rosinger et al.
10,760,946 B2	9/2020	Meier et al.	2008/0289308 A1	11/2008	Brubaker
10,809,118 B1	10/2020	Von Muenster	2008/0312085 A1	12/2008	Kordes et al.
10,830,634 B2	11/2020	Blank et al.	2009/0044505 A1	2/2009	Huster et al.
10,866,109 B2	12/2020	Madsen et al.	2009/0074243 A1	3/2009	Missotten et al.
10,890,922 B2	1/2021	Ramm et al.	2009/0143941 A1	6/2009	Tarasinski et al.
10,909,368 B2	2/2021	Guo et al.	2009/0192654 A1	7/2009	Wendte et al.
10,912,249 B1	2/2021	Wilson	2009/0216410 A1	8/2009	Allen et al.
2002/0011061 A1	1/2002	Lucand et al.	2009/0226036 A1	9/2009	Gaal
2002/0083695 A1	7/2002	Behnke et al.	2009/0259483 A1	10/2009	Hendrickson et al.
2002/0091458 A1	7/2002	Moore	2009/0265098 A1	10/2009	Dix
2002/0099471 A1	7/2002	Benneweis	2009/0306835 A1	12/2009	Ellermann et al.
2002/0133309 A1*	9/2002	Hardt A01D 41/1277 702/129	2009/0311084 A1	12/2009	Coers et al.
2002/0173893 A1	11/2002	Blackmore et al.	2009/0312919 A1	12/2009	Foster et al.
2002/0193928 A1	12/2002	Beck	2009/0312920 A1	12/2009	Boenig et al.
2002/0193929 A1	12/2002	Beck	2009/0325658 A1	12/2009	Phelan et al.
2002/0198654 A1	12/2002	Lange et al.	2010/0036696 A1	2/2010	Lang et al.
2003/0004630 A1	1/2003	Beck	2010/0042297 A1	2/2010	Foster et al.
2003/0014171 A1	1/2003	Ma	2010/0063626 A1	3/2010	Anderson
2003/0024450 A1	2/2003	Juptner	2010/0063648 A1	3/2010	Anderson
2003/0060245 A1	3/2003	Coers et al.	2010/0063651 A1	3/2010	Anderson
2003/0069680 A1	4/2003	Cohen et al.	2010/0063664 A1	3/2010	Anderson
2003/0075145 A1	4/2003	Sheidler et al.	2010/0063954 A1	3/2010	Anderson
2003/0174207 A1	9/2003	Alexia et al.	2010/0070145 A1	3/2010	Foster et al.
2003/0182144 A1	9/2003	Pickett et al.	2010/0071329 A1	3/2010	Hindryckx et al.
2003/0187560 A1	10/2003	Keller et al.	2010/0094481 A1	4/2010	Anderson
2003/0216158 A1*	11/2003	Bischoff A01D 41/127 460/6	2010/0121541 A1	5/2010	Behnke et al.
2003/0229432 A1	12/2003	Ho et al.	2010/0137373 A1	6/2010	Hungenberg et al.
2003/0229433 A1	12/2003	van den Berg et al.	2010/0145572 A1	6/2010	Steckel et al.
2003/0229435 A1	12/2003	Van der Lely	2010/0152270 A1	6/2010	Suty-Heinze et al.
2004/0004544 A1	1/2004	William Knutson	2010/0152943 A1	6/2010	Matthews
2004/0054457 A1	3/2004	Kormann	2010/0217474 A1	8/2010	Baumgarten et al.
2004/0073468 A1	4/2004	Vyas et al.	2010/0268562 A1	10/2010	Anderson
2004/0193348 A1	9/2004	Gray et al.	2010/0268679 A1	10/2010	Anderson
2005/0059445 A1	3/2005	Niermann et al.	2010/0285964 A1	10/2010	Anderson
2005/0066738 A1	3/2005	Moore	2010/0285964 A1	11/2010	Waldruff et al.
2005/0149235 A1	7/2005	Seal et al.	2010/0317517 A1	12/2010	Rosinger et al.
2005/0150202 A1	7/2005	Quick	2010/0319941 A1	12/2010	Peterson
2005/0197175 A1	9/2005	Anderson	2010/0332051 A1	12/2010	Kormann
2005/0241285 A1	11/2005	Maertens et al.	2011/0056178 A1	3/2011	Sauerwein et al.
2005/0283314 A1	12/2005	Hall	2011/0059782 A1	3/2011	Harrington
2005/0284119 A1	12/2005	Brunnert	2011/0072773 A1	3/2011	Schroeder et al.
2006/0014489 A1	1/2006	Fitzner et al.	2011/0084851 A1	4/2011	Peterson et al.
2006/0014643 A1	1/2006	Hacker et al.	2011/0086684 A1*	4/2011	Luellen A01D 41/1277 460/79
2006/0047377 A1	3/2006	Ferguson et al.	2011/0160961 A1	6/2011	Wollenhaupt et al.
2006/0058896 A1	3/2006	Pokorny et al.	2011/0213531 A1	9/2011	Farley et al.
2006/0074560 A1	4/2006	Dyer et al.	2011/0224873 A1	9/2011	Reeve et al.
2006/0155449 A1	7/2006	Dammann	2011/0227745 A1	9/2011	Kikuchi et al.
2006/0162631 A1	7/2006	Hickey et al.	2011/0257850 A1	10/2011	Reeve et al.
2006/0196158 A1	9/2006	Faivre et al.	2011/0270494 A1	11/2011	Imhof et al.
2006/0200334 A1	9/2006	Faivre et al.	2011/0270495 A1	11/2011	Knapp
2007/0005209 A1	1/2007	Fitzner et al.	2011/0295460 A1	12/2011	Hunt et al.
2007/0021948 A1	1/2007	Anderson	2011/0307149 A1	12/2011	Pighi et al.
2007/0056258 A1*	3/2007	Behnke A01D 41/1277 56/10.2 R	2012/0004813 A1	1/2012	Baumgarten et al.
2007/0068238 A1	3/2007	Wendte	2012/0029732 A1	2/2012	Meyer et al.
2007/0073700 A1	3/2007	Wippersteg et al.	2012/0087771 A1	4/2012	Wenzel
2007/0089390 A1	4/2007	Hendrickson et al.	2012/0096827 A1	4/2012	Chaney et al.
2007/0135190 A1	6/2007	Diekhans et al.	2012/0143642 A1	6/2012	O'Neil
2007/0185749 A1	8/2007	Anderson et al.	2012/0215378 A1	8/2012	Sprock et al.
2007/0199903 A1	8/2007	Denny	2012/0215379 A1	8/2012	Sprock et al.
2007/0208510 A1	9/2007	Anderson et al.	2012/0253611 A1	10/2012	Zielke et al.
2007/0233348 A1	10/2007	Diekhans et al.	2012/0263560 A1	10/2012	Diekhans et al.
2007/0233374 A1	10/2007	Diekhans et al.	2012/0265412 A1	10/2012	Diekhans et al.
2007/0239337 A1	10/2007	Anderson	2012/0271489 A1	10/2012	Roberts et al.
2007/0282523 A1	12/2007	Diekhans et al.	2012/0323452 A1	12/2012	Green et al.
2007/0298744 A1	12/2007	Fitzner et al.	2013/0019580 A1	1/2013	Anderson et al.
2008/0030320 A1	2/2008	Wilcox et al.	2013/0022430 A1	1/2013	Anderson et al.
2008/0098035 A1	4/2008	Wippersteg et al.	2013/0046419 A1	2/2013	Anderson
2008/0140431 A1	6/2008	Anderson et al.	2013/0046439 A1	2/2013	Anderson et al.
2008/0177449 A1	7/2008	Pickett et al.	2013/0046525 A1	2/2013	Ali et al.
			2013/0124239 A1	5/2013	Rosa et al.
			2013/0184944 A1	7/2013	Missotten et al.
			2013/0197767 A1	8/2013	Lenz
			2013/0205733 A1	8/2013	Peters
			2013/0210505 A1	8/2013	Bischoff
			2013/0231823 A1	9/2013	Wang et al.
			2013/0319941 A1	12/2013	Schneider

(56)

References Cited

U.S. PATENT DOCUMENTS

2013/0325242	A1	12/2013	Cavender-Bares et al.	2016/0286720	A1	10/2016	Heitmann et al.
2013/0332003	A1	12/2013	Murray et al.	2016/0286721	A1	10/2016	Heitmann et al.
2014/0002489	A1	1/2014	Sauder et al.	2016/0286722	A1	10/2016	Heitmann et al.
2014/0019017	A1	1/2014	Wilken et al.	2016/0309656	A1	10/2016	Wilken et al.
2014/0021598	A1	1/2014	Sutardja	2016/0327535	A1	11/2016	Cotton et al.
2014/0050364	A1	2/2014	Brueckner	2016/0330906	A1	11/2016	Acheson et al.
2014/0067745	A1	3/2014	Avey	2016/0338267	A1	11/2016	Anderson et al.
2014/0121882	A1*	5/2014	Gilmore G05D 1/0295 701/25	2016/0342915	A1	11/2016	Humphrey
				2016/0345485	A1	12/2016	Acheson et al.
				2016/0360697	A1	12/2016	Diaz
				2017/0013773	A1	1/2017	Kirk et al.
				2017/0031365	A1	2/2017	Sugumaran et al.
				2017/0034997	A1	2/2017	Mayerle
2014/0129048	A1	5/2014	Baumgarten et al.	2017/0049045	A1	2/2017	Wilken et al.
2014/0172222	A1	6/2014	Nickel	2017/0055433	A1	3/2017	Jamison
2014/0172224	A1	6/2014	Matthews et al.	2017/0082442	A1	3/2017	Anderson
2014/0172225	A1	6/2014	Matthews et al.	2017/0083024	A1	3/2017	Reijersen Van Buuren
2014/0208870	A1	7/2014	Quaderer et al.	2017/0086381	A1	3/2017	Roell et al.
2014/0215984	A1	8/2014	Bischoff	2017/0089741	A1	3/2017	Takahashi et al.
2014/0230391	A1	8/2014	Hendrickson et al.	2017/0089742	A1	3/2017	Bruns et al.
2014/0230392	A1	8/2014	Dybro et al.	2017/0090068	A1	3/2017	Xiang et al.
2014/0236381	A1	8/2014	Anderson et al.	2017/0105331	A1	4/2017	Herlitzius et al.
2014/0236431	A1	8/2014	Hendrickson et al.	2017/0105335	A1	4/2017	Xu et al.
2014/0257911	A1	9/2014	Anderson	2017/0112049	A1	4/2017	Weisberg et al.
2014/0262547	A1	9/2014	Acheson	2017/0112061	A1	4/2017	Meyer
2014/0277960	A1	9/2014	Blank et al.	2017/0115862	A1	4/2017	Stratton et al.
2014/0297242	A1	10/2014	Sauder et al.	2017/0118915	A1	5/2017	Middelberg et al.
2014/0303814	A1	10/2014	Burema et al.	2017/0124463	A1	5/2017	Chen et al.
2014/0324272	A1	10/2014	Madsen et al.	2017/0127606	A1	5/2017	Horton
2014/0331631	A1	11/2014	Sauder et al.	2017/0160916	A1	6/2017	Baumgarten et al.
2014/0338298	A1	11/2014	Jung et al.	2017/0161627	A1	6/2017	Xu et al.
2014/0350802	A1	11/2014	Biggerstaff et al.	2017/0185086	A1	6/2017	Sauder et al.
2014/0360148	A1*	12/2014	Grosse Wienker A01D 43/14 56/16.8	2017/0188515	A1	7/2017	Baumgarten et al.
				2017/0192431	A1	7/2017	Foster et al.
				2017/0208742	A1	7/2017	Ingibergsson et al.
2015/0049088	A1	2/2015	Snyder et al.	2017/0213141	A1	7/2017	Xu et al.
2015/0088785	A1	3/2015	Chi	2017/0215330	A1	8/2017	Missotten et al.
2015/0095830	A1	4/2015	Massoumi et al.	2017/0223947	A1	8/2017	Gall et al.
2015/0101519	A1	4/2015	Blackwell et al.	2017/0227969	A1	8/2017	Murray et al.
2015/0105984	A1	4/2015	Birrell et al.	2017/0235471	A1	8/2017	Scholer et al.
2015/0124054	A1	5/2015	Darr et al.	2017/0245434	A1	8/2017	Jung et al.
2015/0168187	A1	6/2015	Myers	2017/0251600	A1	9/2017	Anderson et al.
2015/0211199	A1	7/2015	Corcoran et al.	2017/0270446	A1	9/2017	Starr et al.
2015/0230403	A1	8/2015	Jung et al.	2017/0270616	A1	9/2017	Basso
2015/0242799	A1	8/2015	Seki et al.	2017/0316692	A1	11/2017	Rusciolelli et al.
2015/0243114	A1	8/2015	Tanabe et al.	2017/0318743	A1	11/2017	Sauder et al.
2015/0254800	A1	9/2015	Johnson et al.	2017/0322550	A1	11/2017	Yokoyama
2015/0264863	A1	9/2015	Muench et al.	2017/0332551	A1	11/2017	Todd et al.
2015/0276794	A1	10/2015	Pistol et al.	2017/0336787	A1	11/2017	Pichlmaier et al.
2015/0278640	A1	10/2015	Johnson et al.	2017/0370765	A1	12/2017	Meier et al.
2015/0285647	A1	10/2015	Meyer Zu Helligen et al.	2018/0000011	A1	1/2018	Schleusner et al.
2015/0293029	A1	10/2015	Acheson et al.	2018/0014452	A1	1/2018	Starr
2015/0302305	A1	10/2015	Rupp et al.	2018/0022559	A1	1/2018	Knutson
2015/0305238	A1	10/2015	Klausmann et al.	2018/0024549	A1	1/2018	Hurd
2015/0305239	A1	10/2015	Jung	2018/0035622	A1	2/2018	Gresch et al.
2015/0327440	A1	11/2015	Dybro et al.	2018/0054955	A1	3/2018	Oliver
2015/0351320	A1	12/2015	Takahara et al.	2018/0060975	A1	3/2018	Hassanzadeh
2015/0370935	A1	12/2015	Starr	2018/0070534	A1	3/2018	Mayerle
2015/0373902	A1	12/2015	Pasquier	2018/0077865	A1	3/2018	Gallmeier
2015/0379785	A1	12/2015	Brown., Jr. et al.	2018/0084709	A1	3/2018	Wieckhorst et al.
2016/0025531	A1	1/2016	Bischoff et al.	2018/0084722	A1	3/2018	Wieckhorst et al.
2016/0029558	A1	2/2016	Dybro et al.	2018/0092301	A1	4/2018	Vandike et al.
2016/0052525	A1	2/2016	Tuncer et al.	2018/0092302	A1	4/2018	Vandike et al.
2016/0057922	A1	3/2016	Freiberg et al.	2018/0108123	A1	4/2018	Baurer et al.
2016/0066505	A1	3/2016	Bakke et al.	2018/0120133	A1	5/2018	Blank et al.
2016/0073573	A1	3/2016	Ethington et al.	2018/0121821	A1	5/2018	Parsons et al.
2016/0078375	A1	3/2016	Ethington et al.	2018/0124992	A1	5/2018	Koch et al.
2016/0078570	A1	3/2016	Ethington et al.	2018/0129879	A1	5/2018	Achtelik et al.
2016/0088794	A1	3/2016	Baumgarten et al.	2018/0132422	A1	5/2018	Hassanzadeh et al.
2016/0106038	A1	4/2016	Boyd et al.	2018/0136664	A1	5/2018	Tomita et al.
2016/0084813	A1	5/2016	Anderson et al.	2018/0146612	A1	5/2018	Sauder et al.
2016/0146611	A1	5/2016	Matthews	2018/0146624	A1	5/2018	Chen et al.
2016/0202227	A1	7/2016	Mathur et al.	2018/0153084	A1	6/2018	Calleija et al.
2016/0203657	A1	7/2016	Bell et al.	2018/0177125	A1	6/2018	Takahara et al.
2016/0212939	A1	7/2016	Ouchida et al.	2018/0181893	A1	6/2018	Basso
2016/0215994	A1	7/2016	Mewes et al.	2018/0196438	A1	7/2018	Newlin et al.
2016/0232621	A1	8/2016	Ethington et al.	2018/0196441	A1	7/2018	Muench et al.
2016/0247075	A1	8/2016	Mewes et al.	2018/0211156	A1	7/2018	Guan et al.
2016/0247082	A1	8/2016	Stehling	2018/0232674	A1	8/2018	Bilde
2016/0260021	A1	9/2016	Marek				

(56)

References Cited

U.S. PATENT DOCUMENTS

2018/0242523 A1 8/2018 Kirchbeck et al.
 2018/0249641 A1 9/2018 Lewis et al.
 2018/0257657 A1 9/2018 Blank et al.
 2018/0271015 A1 9/2018 Redden et al.
 2018/0279599 A1 10/2018 Struve
 2018/0295771 A1 10/2018 Peters
 2018/0310474 A1 11/2018 Posselius et al.
 2018/0317381 A1 11/2018 Bassett
 2018/0317385 A1 11/2018 Wellensiek et al.
 2018/0325012 A1 11/2018 Ferrari et al.
 2018/0325014 A1 11/2018 Debbaut
 2018/0338422 A1 11/2018 Brubaker
 2018/0340845 A1 11/2018 Rhodes et al.
 2018/0359917 A1 12/2018 Blank et al.
 2018/0359919 A1 12/2018 Blank et al.
 2018/0364726 A1 12/2018 Foster et al.
 2019/0021226 A1 1/2019 Dima et al.
 2019/0025175 A1 1/2019 Laugwitz
 2019/0050948 A1 2/2019 Perry et al.
 2019/0057460 A1 2/2019 Sakaguchi et al.
 2019/0066234 A1 2/2019 Bedoya et al.
 2019/0069470 A1 3/2019 Pfeiffer et al.
 2019/0075727 A1 3/2019 Duke et al.
 2019/0085785 A1 3/2019 Abolt
 2019/0090423 A1 3/2019 Escher et al.
 2019/0098825 A1 4/2019 Neitemeier et al.
 2019/0104722 A1 4/2019 Slaughter et al.
 2019/0108413 A1 4/2019 Chen et al.
 2019/0114847 A1 4/2019 Wagner et al.
 2019/0124819 A1 5/2019 Madsen et al.
 2019/0129430 A1 5/2019 Madsen et al.
 2019/0136491 A1 5/2019 Martin et al.
 2019/0138962 A1 5/2019 Ehlmann et al.
 2019/0147094 A1 5/2019 Zhan et al.
 2019/0147249 A1 5/2019 Kiepe et al.
 2019/0156255 A1 5/2019 Carroll
 2019/0174667 A1 6/2019 Gresch et al.
 2019/0183047 A1 6/2019 Dybro et al.
 2019/0200522 A1 7/2019 Hansen et al.
 2019/0230855 A1 8/2019 Reed et al.
 2019/0239416 A1 8/2019 Green et al.
 2019/0261550 A1 8/2019 Damme et al.
 2019/0261559 A1 8/2019 Heitmann et al.
 2019/0261560 A1 8/2019 Jelenkovic
 2019/0313570 A1 10/2019 Owechko
 2019/0327889 A1 10/2019 Borgstadt
 2019/0327892 A1 10/2019 Fries et al.
 2019/0335662 A1 11/2019 Good et al.
 2019/0335674 A1 11/2019 Basso
 2019/0343035 A1 11/2019 Smith et al.
 2019/0343043 A1 11/2019 Bormann et al.
 2019/0343044 A1 11/2019 Bormann et al.
 2019/0343048 A1 11/2019 Farley et al.
 2019/0351765 A1 11/2019 Rabusic
 2019/0354081 A1 11/2019 Blank et al.
 2019/0364733 A1 12/2019 Laugen et al.
 2019/0364734 A1 12/2019 Kriebel et al.
 2020/0000006 A1 1/2020 Mcdonald et al.
 2020/0008351 A1 1/2020 Zielke et al.
 2020/0015416 A1 1/2020 Barther et al.
 2020/0019159 A1 1/2020 Kocer et al.
 2020/0024102 A1 1/2020 Brill et al.
 2020/0029488 A1 1/2020 Bertucci et al.
 2020/0034759 A1 1/2020 Dumstorff et al.
 2020/0037491 A1 2/2020 Schoeny et al.
 2020/0053961 A1 2/2020 Dix et al.
 2020/0064144 A1 2/2020 Tomita et al.
 2020/0064863 A1 2/2020 Tomita et al.
 2020/0074023 A1 3/2020 Nizami et al.
 2020/0084963 A1 3/2020 Gururajan et al.
 2020/0084966 A1 3/2020 Corban et al.
 2020/0090094 A1 3/2020 Blank
 2020/0097851 A1 3/2020 Alvarez et al.
 2020/0113142 A1 4/2020 Coleman et al.
 2020/0125822 A1 4/2020 Yang et al.

2020/0128732 A1 4/2020 Chaney
 2020/0128733 A1 4/2020 Vandike et al.
 2020/0128734 A1 4/2020 Brammeier et al.
 2020/0128735 A1 4/2020 Bonefas et al.
 2020/0128737 A1 4/2020 Anderson et al.
 2020/0128738 A1 4/2020 Suleman et al.
 2020/0128740 A1 4/2020 Suleman
 2020/0133262 A1 4/2020 Suleman et al.
 2020/0141784 A1 5/2020 Lange et al.
 2020/0146203 A1 5/2020 Deng
 2020/0150631 A1 5/2020 Frieberg et al.
 2020/0154639 A1 5/2020 Takahara et al.
 2020/0163277 A1 5/2020 Cooksey et al.
 2020/0183406 A1 6/2020 Borgstadt
 2020/0187409 A1 6/2020 Meyer Zu Hellingen
 2020/0196526 A1 6/2020 Koch et al.
 2020/0202596 A1 6/2020 Kitahara et al.
 2020/0221632 A1 7/2020 Strnad et al.
 2020/0221635 A1 7/2020 Hendrickson et al.
 2020/0221636 A1 7/2020 Boydens et al.
 2020/0265527 A1 8/2020 Rose et al.
 2020/0317114 A1 10/2020 Hoff
 2020/0319632 A1 10/2020 Desai et al.
 2020/0319655 A1 10/2020 Desai et al.
 2020/0323133 A1 10/2020 Anderson et al.
 2020/0323134 A1 10/2020 Darr et al.
 2020/0326674 A1 10/2020 Palla et al.
 2020/0326727 A1 10/2020 Palla et al.
 2020/0333278 A1 10/2020 Locken et al.
 2020/0337232 A1 10/2020 Blank et al.
 2020/0352099 A1 11/2020 Meier et al.
 2020/0359547 A1 11/2020 Sakaguchi et al.
 2020/0359549 A1 11/2020 Sakaguchi et al.
 2020/0363256 A1 11/2020 Meier et al.
 2020/0375083 A1 12/2020 Anderson et al.
 2020/0375084 A1 12/2020 Sakaguchi et al.
 2020/0378088 A1 12/2020 Anderson
 2020/0404842 A1 12/2020 Dugas et al.
 2021/0015041 A1 1/2021 Bormann et al.
 2021/0176916 A1 6/2021 Sidon et al.
 2021/0176918 A1 6/2021 Franzen et al.

FOREIGN PATENT DOCUMENTS

BR PI0502658 A 2/2007
 BR PI0802384 A2 3/2010
 BR PI1100258 A2 3/2014
 BR 102014007178 A2 8/2016
 CA 1165300 A 4/1984
 CA 2283767 A1 3/2001
 CA 2330979 A1 8/2001
 CA 2629555 A1 11/2009
 CA 135611 S 5/2011
 CN 2451633 Y 10/2001
 CN 101236188 A 8/2008
 CN 100416590 C 9/2008
 CN 101303338 A 11/2008
 CN 101363833 A 2/2009
 CN 201218789 Y 4/2009
 CN 101839906 A 9/2010
 CN 101929166 A 12/2010
 CN 102080373 A 6/2011
 CN 102138383 A 8/2011
 CN 102277867 B 12/2011
 CN 202110103 U 1/2012
 CN 202119772 U 1/2012
 CN 202340435 U 7/2012
 CN 103088807 A 5/2013
 CN 103181263 A 7/2013
 CN 203053961 U 7/2013
 CN 203055121 U 7/2013
 CN 203206739 U 9/2013
 CN 102277867 B 10/2013
 CN 203275401 U 11/2013
 CN 203613525 U 5/2014
 CN 203658201 U 6/2014
 CN 103954738 A 7/2014
 CN 203741803 U 7/2014
 CN 204000818 U 12/2014

(56)

References Cited

FOREIGN PATENT DOCUMENTS

CN	204435344	U	7/2015	DE	102013212151	A1	12/2014
CN	204475304	U	7/2015	DE	102013019098	B3	1/2015
CN	105205248	A	12/2015	DE	102014108449	A1	2/2015
CN	204989174	U	1/2016	DE	2014201203	A1	7/2015
CN	105432228	A	3/2016	DE	102014208068	A1	10/2015
CN	105741180	A	7/2016	DE	102015006398	B3	5/2016
CN	106053330	A	10/2016	DE	102015109799	A1	12/2016
CN	106198877	A	12/2016	DE	112015002194	T5	1/2017
CN	106198879	A	12/2016	DE	102017204511	A1	9/2018
CN	106226470	A	12/2016	DE	102019114872	A1	12/2020
CN	106248873	A	12/2016	EP	0070219	B1	10/1984
CN	106290800	A	1/2017	EP	0355049	A2	2/1990
CN	106327349	A	1/2017	EP	845198	B2	6/1998
CN	106644663	A	5/2017	EP	0532146	B1	8/1998
CN	206330815	U	7/2017	EP	1444879	A1	8/2004
CN	206515118	U	9/2017	EP	1219159	B1	6/2005
CN	206515119	U	9/2017	EP	1219153	B1	2/2006
CN	206616118	U	11/2017	EP	1692928	A2	8/2006
CN	206696107		12/2017	EP	1574122	B1	2/2008
CN	206696107	U	12/2017	EP	1943877	A2	7/2008
CN	107576674		1/2018	EP	1598586	B1	9/2009
CN	107576674	A	1/2018	EP	1731983	B1	9/2009
CN	206906093	U	1/2018	EP	2146307	A2	1/2010
CN	206941558		1/2018	EP	0845198	B2	2/2010
CN	206941558	U	1/2018	EP	2186389	A1	5/2010
CN	107736088	A	2/2018	EP	2267566	A2	12/2010
CN	107795095	A	3/2018	EP	3491192	A2	12/2010
CN	207079558		3/2018	EP	2057884	B1	1/2011
CN	107941286	A	4/2018	EP	2146307	B1	5/2012
CN	107957408	A	4/2018	EP	2446732	A1	5/2012
CN	108009542	A	5/2018	EP	2524586	A2	11/2012
CN	108304796	A	7/2018	EP	2529610	A1	12/2012
CN	207567744	U	7/2018	EP	2243353	B1	3/2013
CN	108614089	A	10/2018	EP	2174537	B1	5/2013
CN	208013131	U	10/2018	EP	2592919	A1	5/2013
CN	108881825	A	11/2018	EP	1674324	B2	5/2014
CN	208047351	U	11/2018	EP	2759829	A1	7/2014
CN	109357804	A	2/2019	EP	2764764	B1	8/2014
CN	109485353	A	3/2019	EP	2267566	A3	12/2014
CN	109633127	A	4/2019	EP	2191439	B1	3/2015
CN	109763476	A	5/2019	EP	2586286	B1	3/2015
CN	109961024	A	7/2019	EP	2592919	B1	9/2015
CN	110262287	A	9/2019	EP	2921042	A1	9/2015
CN	110720302	A	1/2020	EP	2944725	A1	11/2015
CN	111201879	A	5/2020	EP	2764764	B1	12/2015
CN	210585958	U	5/2020	EP	2510777	B1	3/2016
CN	111406505	A	7/2020	EP	2997805	A1	3/2016
CS	247426	B1	12/1986	EP	3000302	A1	3/2016
CS	248318	B1	2/1987	EP	2868806	B1	7/2016
CZ	17266	U1	2/2007	EP	3085221	A1	10/2016
CZ	20252	U1	11/2009	EP	3095310	A1	11/2016
DE	2354828	A1	5/1975	EP	3097759	A1	11/2016
DE	152380	A1	11/1981	EP	2452551	B1	5/2017
DE	3728669	A1	3/1989	EP	3175691	A1	6/2017
DE	4431824	C1	5/1996	EP	3195719	A1	7/2017
DE	19509496	A1	9/1996	EP	3195720	A1	7/2017
DE	19528663	A1	2/1997	EP	3259976	A1	12/2017
DE	19718455	A1	11/1997	EP	3262934	A1	1/2018
DE	19705842	A1	8/1998	EP	3491192	A1	1/2018
DE	19828355	A1	1/2000	EP	3287007	A1	2/2018
DE	10050224	A1	4/2002	EP	3298876	A1	3/2018
DE	10120173	A1	10/2002	EP	3300579	A1	4/2018
DE	202004015141	U1	12/2004	EP	3315005	A1	5/2018
DE	102005000770	B3	7/2006	EP	3316208	A1	5/2018
DE	102005000771	A1	8/2006	EP	2829171	B1	6/2018
DE	102008021785	A1	11/2009	EP	2508057		7/2018
DE	102009041646	A1	3/2011	EP	2508057	B1	7/2018
DE	102010004648	A1	7/2011	EP	3378298	A1	9/2018
DE	102010038661	A1	2/2012	EP	3378299	A1	9/2018
DE	102011005400	A1	9/2012	EP	2997805	A1	10/2018
DE	202012103730	U1	10/2012	EP	3384754	A1	10/2018
DE	102011052688	A1	2/2013	EP	3289853	B1	3/2019
DE	102012211001	A1	1/2014	EP	3456167	A1	3/2019
DE	102012220109	A1 *	5/2014	EP	3466239	A1	4/2019
DE	102012223768	A1 *	6/2014	EP	3469878	A1	4/2019
		 G07C 5/085	EP	3289852	B1	6/2019
		 A01D 75/187	EP	3491192	A1	6/2019
				EP	3494770	A1	6/2019
				EP	3498074	A1	6/2019

(56)

References Cited

FOREIGN PATENT DOCUMENTS

EP	3000302	B1	8/2019	MX	GT06000012	A	1/2008
EP	3533314	A1	9/2019	PL	178299	B1	4/2000
EP	3569049	A1	11/2019	RO	130713		11/2015
EP	3000307	B1	12/2019	RU	1791767	C	1/1993
EP	3586592	A2	1/2020	RU	2005102554	A	7/2006
EP	3593613	A1	1/2020	RU	2421744	C	6/2011
EP	3593620	A1	1/2020	RU	2421744	C1	6/2011
EP	3613272	A1	2/2020	RU	2502047	C	12/2013
EP	3243374	B1	3/2020	RU	2502047	C1	12/2013
EP	3626038	A1	3/2020	RU	164128		8/2016
EP	3259976	B1	4/2020	RU	2017114139	A	4/2017
EP	3635647	A1	4/2020	RU	2017114139	A	10/2018
EP	3378298	B1	5/2020	RU	2017114139	A3	5/2019
EP	3646699	A1	5/2020	SU	834514	A1	5/1981
EP	3662741	A1	6/2020	SU	887717	A1	12/1981
EP	3685648	A1	7/2020	SU	1052940	A1	11/1983
EP	2995191	B2	10/2020	SU	1134669	A1	1/1985
ES	2116215	A1	7/1998	SU	1526588	A1	12/1989
ES	2311322	A1	2/2009	SU	1761864	A1	9/1992
FI	5533	A	11/1913	WO	1986005353	A1	9/1986
FR	1451480	A	1/1966	WO	2001052160	A1	7/2001
FR	2817344	A1	5/2002	WO	2002015673	A1	2/2002
FR	2901291	A	11/2007	WO	2003005803	A1	1/2003
FR	2901291	A1	11/2007	WO	2007050192	A2	5/2007
GB	901081	A	7/1962	WO	2009156542	A1	12/2009
GB	201519517	A1	5/2017	WO	2010003421	A1	1/2010
IN	01632DE2014	A	8/2016	WO	2011104085	A1	9/2011
IN	1632DE2014	A	8/2016	WO	2012041621	A1	4/2012
IN	201641027017	A	10/2016	WO	2012110508	A1	8/2012
IN	202041039250	A	9/2020	WO	2012110544	A1	8/2012
JP	S60253617	A	12/1985	WO	2013063106	A2	5/2013
JP	S63308110	A	12/1988	WO	2013079247	A1	6/2013
JP	H02196960	A	8/1990	WO	2013086351	A1	6/2013
JP	H02215311	A	8/1990	WO	2013087275	A1	6/2013
JP	H0779681	A	3/1995	WO	2014046685	A1	3/2014
JP	H1066436	A	3/1998	WO	2014093814	A1	6/2014
JP	H10191762	A	7/1998	WO	2014195302	A1	12/2014
JP	2000352044	A	12/2000	WO	2014195302	A1	12/2014
JP	2001057809	A	3/2001	WO	2015038751	A1	3/2015
JP	2002186348	A	7/2002	WO	2015153809	A1	10/2015
JP	2005227233	A	8/2005	WO	16020595	A1	2/2016
JP	2006166871	A	6/2006	WO	2016020595	A1	2/2016
JP	2011205967	A	10/2011	WO	2016118686	A1	7/2016
JP	2015070812	A	4/2015	WO	2017008161	A1	1/2017
JP	2015151826	A	8/2015	WO	2017008161	A1	1/2017
JP	2015219651	A	12/2015	WO	2017060168	A1	4/2017
JP	2016071726	A	5/2016	WO	2017077113	A1	5/2017
JP	2016160808	A	9/2016	WO	2017096489	A1	6/2017
JP	6087258	B2	3/2017	WO	2017099570	A1	6/2017
JP	2017136035	A	8/2017	WO	2017116913	A1	7/2017
JP	2017137729	A	8/2017	WO	2017116913	A1	7/2017
JP	2017195804	A	11/2017	WO	2017170507	A1	10/2017
JP	2018068284	A	5/2018	WO	2017205406	A1	11/2017
JP	2018102154	A	7/2018	WO	2017205410	A1	11/2017
JP	2018151388	A	9/2018	WO	2018043336	A1	3/2018
JP	2019004796	A	1/2019	WO	2018073060	A1	4/2018
JP	2019129744	A	8/2019	WO	2018081759	A1	5/2018
JP	2019146506	A	9/2019	WO	2018116772	A1	6/2018
JP	2019216744	A	12/2019	WO	2018142768	A1	8/2018
JP	2020018255	A	2/2020	WO	2018200870	A1	11/2018
JP	2020031607	A	3/2020	WO	2018206587	A1	11/2018
JP	2020113062	A	7/2020	WO	2018220159	A1	12/2018
JP	2020127405	A	8/2020	WO	2018226139	A1	12/2018
KR	100974892		8/2010	WO	2018235486	A1	12/2018
KR	100974892	B1	8/2010	WO	2018235942	A1	12/2018
KR	20110018582	A	2/2011	WO	2018235942	A1	12/2018
KR	101067576	B	9/2011	WO	WO18235486	A1	12/2018
KR	101067576	B1	9/2011	WO	2019034213	A1	2/2019
KR	101134075	B1	4/2012	WO	2019079205	A1	4/2019
KR	101447197	B1	10/2014	WO	2019081349	A1	5/2019
KR	101653750		9/2016	WO	2019091535	A1	5/2019
KR	20170041377	A	4/2017	WO	2019109191	A1	6/2019
KR	200485051	Y	11/2017	WO	2019124225	A1	6/2019
KR	200485051	Y1	11/2017	WO	2019129333	A1	7/2019
KR	101873657	B	8/2018	WO	2019129334	A1	7/2019
				WO	2019129335	A1	7/2019
				WO	2019215185	A1	11/2019
				WO	2019230358	A1	12/2019
				WO	2020026578	A1	2/2020
				WO	2020026650	A1	2/2020

(56)

References Cited

FOREIGN PATENT DOCUMENTS

WO	2020026651	A1	2/2020
WO	2020031473	A1	2/2020
WO	2020038810	A1	2/2020
WO	2020039312	A1	2/2020
WO	2020039671	A1	2/2020
WO	2020044726	A1	3/2020
WO	2020082182	A1	4/2020
WO	2020100810	A1	5/2020
WO	2020110920	A1	6/2020
WO	2020195007	A1	10/2020
WO	2020206941	A1	10/2020
WO	2020206942	A1	10/2020
WO	2020210607	A1	10/2020
WO	2020221981	A1	11/2020

OTHER PUBLICATIONS

- Feng-jie et al., "Crop Area Yield Risk Evaluation and Premium Rates Calculation—Based on Nonparametric Kernel Density Estimation," 2009, Publisher: IEEE.*
- Ruiying et al., "Random Fuzzy Production and Distribution Plan of Agricultural Products and Its PSO Algorithm," 2014, Publisher: IEEE.*
- S. Veenadhari et al., "Machine Learning Approach for Forecasting Crop Yield Based on Climatic Parameters", 2014 International Conference on Computer Communication and Informatics (ICCCI-2014) Jan. 3-5, 2014, Coimbatore, India, 5 pages.
- Fernandez-Quintanilla et al., "Is the current state of the art of weed monitoring suitable for site-specific weed management in arable crops?", First Published May 1, 2018, 4 pages.
- Application and Drawings for U.S. Appl. No. 17/067,483, filed Oct. 9, 2020, 63 pages.
- Application and Drawings for U.S. Appl. No. 17/066,442, filed Oct. 8, 2020, 65 pages.
- Application and Drawings for U.S. Appl. No. 17/066,444, filed Oct. 8, 2020, 102 pages.
- Application and Drawings for U.S. Appl. No. 17/066,999, filed Oct. 9, 2020, 67 pages.
- European Search Report issued in European Patent Application No. 19205142.3 dated Feb. 28, 2020 (6 pages).
- Huang, Z., Chen, J., Dong, J., Li, Y. and Zhan, Z., Sep. 2010, Research of the combine harvester load feedback control system using multi-signal fusion method and fuzzy algorithm. In 2010 World Automation Congress (pp. 57-61). IEEE.
- Hermann, D., Bilde, M.L., Andersen, N.A. and Ravn, O., Aug. 2017, On-the-go throughput prediction in a combine harvester using sensor fusion. In 2017 IEEE Conference on Control Technology and Applications (CCTA) (pp. 67-72).
- Notice of Allowance for U.S. Appl. No. 16/171,978 dated Dec. 15, 2020, 8 pages.
- Application and Drawings for U.S. Appl. No. 16/171,078, filed Oct. 26, 2018, 53 pages.
- Shih, Mei-Ju, Guan-Yu Lin, and Hung-Yu Wei. "Two paradigms in cellular Internet-of-Things access for energy-harvesting machine-to-machine devices: Push-based versus pull-based." IET Wireless Sensor Systems 6.4 (2016): 121-129.
- Liu, Yi, et al. "An efficient MAC protocol with adaptive energy harvesting for machine-to-machine networks." IEEE access 3 (2015): 358-367.
- Application and Drawings for U.S. Appl. No. 16/175,993, filed Oct. 31, 2018, 28 pages.
- Application and Drawings for U.S. Appl. No. 16/380,623, filed Apr. 10, 2019, 36 pages.
- Application and Drawings for U.S. Appl. No. 16/783,511, filed Feb. 6, 2020, 55 pages.
- "Automated Weed Detection With Drones" dated May 25, 2017, retrieved at: <<<https://www.precisionhawk.com/blog/media/topic/automated-weed-identification-with-drones>>>, retrieved on Jan. 21, 2020, 4 pages.
- F. Forcella, "Estimating the Timing of Weed Emergence", Site-Specific Management Guidelines, retrieved at: <<[http://www.ipni.net/publication/ssmg.nsf/0/D26EC9A906F9B8C9852579E500773936/\\$FILE/SSMG-20.pdf](http://www.ipni.net/publication/ssmg.nsf/0/D26EC9A906F9B8C9852579E500773936/$FILE/SSMG-20.pdf)>>, retrieved on Jan. 21, 2020, 4 pages.
- Chauhan et al., "Emerging Challenges and Opportunities for Education and Research in Weed Science", *frontiers in Plant Science*. Published online Sep. 5, 2017, 22 pages.
- Apan, A., Wells, N., Reardon-Smith, K., Richardson, L., McDougall, K., and Basnet, B.B., 2008. Predictive mapping of blackberry in the Condamine Catchment using logistic regression and spatial analysis. In *Proceedings of the 2008 Queensland Spatial Conference: Global Warning: What's Happening in Paradise*. Spatial Sciences Institute.
- Jarnevich, C.S., Holcombe, T.R., Barnett, D.T., Stohlgren, T.J. and Kartesz, J.T., 2010. Forecasting weed distributions using climate data: a GIS early warning tool. *Invasive Plant Science and Management*. 3(4), pp. 365-375.
- Sa et al., "WeedMap: A Large-Scale Semantic Weed Mapping Framework Using Aerial Multispectral Imaging and Deep Neural Network for Precision Farming", Sep. 6, 2018, 25 pages.
- Pflanz et al., "Weed Mapping with UAS Imagery and a Bag of Visual Words Based Image Classifier", Published Sep. 24, 2018, 28 pages.
- Application and Drawings for U.S. Appl. No. 62/928,964, filed Oct. 31, 2019, 14 pages.
- Application and Drawings for U.S. Appl. No. 16/783,475, filed Feb. 6, 2020, 55 pages.
- U.S. Appl. No. 17/067,483 Application and Drawings as filed Oct. 9, 2020, 63 pages.
- U.S. Appl. No. 17/066,442 Application and Drawings as filed Oct. 8, 2020, 65 pages.
- U.S. Appl. No. 16/380,550, filed Apr. 10, 2019, Application and Drawings, 47 pages.
- U.S. Appl. No. 17/066,999 Application and Drawings as filed Oct. 9, 2020, 67 pages.
- U.S. Appl. No. 17/066,444 Application and Drawings as filed Oct. 8, 2020, 102 pages.
- Extended Search Report for European Patent Application No. 20167930.5 dated Sep. 15, 2020, 8 pages.
- Extended Search Report for European Patent Application No. 19205901.2 dated Mar. 17, 2020, 6 pages.
- Notice of Allowance for U.S. Appl. No. 16/171,978, dated Dec. 15, 2020, 21 pages.
- Zhigen et al., "Research of the Combine Harvester Load Feedback Control System Using Multi-Signal Fusion Method and Duzzy Algorithm," 2010, Publisher: IEEE.
- Dan et al., "On-the-go Throughtout Prediction in a Combine Harvester Using Sensor Fusion," 2017, Publisher: IEEE.
- Fernandez-Quintanilla et al., "Is the current state of the art of weed monitoring suitable for site-specific weed management in arable crops?", First Published May 1, 2018, 4 pages.
- Dionysis Bochtis et al. "Field Operations Planning for Agricultural Vehicles: A Hierarchical Modeling Framework." *Agricultural Engineering International: the CIGR Ejournal*. Manuscript PM 06 021. vol. IX. Feb. 2007, pp. 1-11.
- U.S. Appl. No. 16/432,557, filed Jun. 5, 2019, 61 pages.
- European Search Report issued in counterpart European Patent Application No. 19205142.3 dated Feb. 28, 2020 (pages).
- Mei-Ju et al., "Two paradigms in cellular Internet-of-Things access for energy-harvesting machine-to-machine devices: push-based versus pull-based," 2016, vol. 6.
- Yi et al., "An Efficient MAC Protocol With Adaptive Energy Harvesting for Machine-to-Machine Networks," 2015, vol. 3, Publisher: IEEE.
- Application and Drawings for U.S. Appl. No. 16/171,978, filed Oct. 26, 2018, 53 pages.
- European Search Report issued in European Patent Application No. 19203883.4 dated Mar. 23, 2020 (10 pages).
- Notice of Allowance for U.S. Appl. No. 16/171,978 dated Oct. 28, 2020, 5 pages.
- Notice of Allowance for U.S. Appl. No. 16/171,978, dated Aug. 7, 2020, 9 pages.

(56)

References Cited

OTHER PUBLICATIONS

- K.R. Manjunath et al., "Developing Spectral Library of Major Plant Species of Western Himalayas Using Ground Observations", *J. Indian Soc Remote Sen* (Mar. 2014) 42(a):201-216, 17 pages.
- U.S. Appl. No. 16/380,564 Application and Drawings as filed Apr. 10, 2019, 55 pages.
- S. Veenadhari et al., "Machine Learning Approach for Forecasting Crop Yield Based on Climatic Parameters", 2014 International Conference on Computer Communication and Informatics (ICCCI-2014) Jan. 3-6, 2014, Coimbatore, India, 5 pages.
- Non-Final Office Action for U.S. Appl. No. 16/380,531 dated Oct. 21, 2020, 10 pages.
- U.S. Appl. No. 16/380,531 Application and Drawings as filed Apr. 10, 2019, 46 pages.
- Leu et al., *Grazing Corn Residue Using Resources and Reducing Costs*, Aug. 2009, 4 pages.
- "No-Till Soils", *Soil Heath Brochure*, 2 pages, last accessed Jul. 14, 2020.
- Strickland et al., "Nitrate Toxicity in Livestock" Oklahoma State University, Feb. 2017, 2 pages.
- Strickland et al., "Nitrate Toxicity in Livestock" Oklahoma State University, 8 pages, Feb. 2017.
- Brownlee, "Neural Networks are Function Approximation Algorithms", Mar. 18, 2020, 13 pages.
- Thompson, "Morning glory can make it impossible to harvest corn", Feb. 19, 2015, 3 pages.
- Tumilson, "Monitoring Growth Development and Yield Estimation of Maize Using Very High-resolution Uavimages in Gronau, Germany", Feb. 2017, 63 pages.
- Hunt, "Mapping Weed Infestations Using Remote Sensing", 8 pages, Jul. 19, 2005.
- Wright, et al., "Managing Grain Protein in Wheat Using Remote Sensing", 12 pages, 2003.
- "Malting Barley in Pennsylvania", *Agronomy Facts* 77, 6 pages, Code EE0179 Jun. 2016.
- "Green stem syndrome in soybeans", *Agronomy eUpdate Issue* 478 Oct. 10, 2014, 3 pages.
- "Keep Weed Seed Out of Your Harvest", Aug. 8, 2019, 1 pages.
- Hodrius et al., "The Impact of Multi-Sensor Data Assimilation on Plant Parameter Retrieval and Yield Estimation for Sugar Beet", *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XL-7/W3, 2015, 36th International Symposium on Remote Sensing of Environment, May 11-15, 2015, Berlin, Germany, 7 pages.
- Fernandez-Quintanilla et al., "Is the current state of the art of weed monitoring suitable for site-specific weed management in arable crops?", Feb. 2018, 35 pages.
- Anonymous, "Improved System and Method for Controlling Agricultural Vehicle Operation Using Historical Data", Dec. 16, 2009, 8 pages.
- Anonymous, "System and Method for Controlling Agricultural Vehicle Operation Using Historical Data", Jun. 30, 2009, 8 pages.
- "Leafsnap, a new mobile app that identifies plants by leaf shape, is launched by Smithsonian and collaborators", May 2, 2011, 5 pages. Insect Gallery, Department of Entomology, Kansas State University, Oct. 19, 2020, 8 pages.
- Licht, "Influence of Corn Seeding Rate, Soil Attributes, and Topographic Characteristics on Grain Yield, Yield Components, and Grain Composition", 2015, 107 pages.
- "Notice of Retraction Virtual simulation of plant with individual stem based on crop growth model", Mar. 5, 2017, 7 pages.
- Ma et al., "Identification of Fusarium Head Blight in Winter Wheat Ears Using Continuous Wavelet Analysis", Dec. 19, 2019, 15 pages.
- Leland, "Who Did that? Identifying Insect Damage", Apr. 1, 2015, 4 pages.
- "How to improve maize protein content" <https://www.yara.co.uk/crop-nutrition/forage-maize/improving-maize-protein-content>, Sep. 30, 2020, 10 pages.
- Hafemeister, "Weed control at harvest, combines are ideal vehicles for spreading weed seeds", Sep. 25, 2019, 3 pages.
- "Harvesting Tips", Northern Pulse Growers Association, 9 pages, Jan 31, 2001.
- Wortmann et al., "Harvesting Crop Residues", Aug. 10, 2020, 8 pages.
- "Harvesting", Oklahoma State University, *Canola Swathing Guide*, 2010, 9 pages, last accessed Jul. 14, 2020.
- Hanna, "Harvest Tips for Lodged Corn", Sep. 6, 2011, 3 pages.
- "Green Weeds Complicate Harvest", *Crops, Slider*, Sep. 26, 2012, 2 pages.
- "Agrowatch Green Vegetation Index", Retrieved Dec. 11, 2020, 4 pages.
- "Grazing Corn Residues" (<http://www.ca.uky.edu>), 3 pages, Aug. 24, 2009.
- Jarnevich et al., *Forecasting Weed Distributions Using Climate Data: A GIS Early Warning Tool*, Downloaded on Jul. 13, 2020, 12 pages.
- Combine Cutting and Feeding Mechanisms in the Southeast, by J-K Park, Agricultural Research Service, U.S. Dept. of Agriculture, 1963, 1 page.
- Hartzler, "Fate of weed seeds in the soil", 4 pages, Jan 31, 2001.
- Digman, "Combine Considerations for a Wet Corn Harvest", Extension Specialist UW—Madison, 3 pages, Oct. 29, 2009.
- S-Series Combine and Front End Equipment Optimization, John Deere Harvester Works, 20 pages Date: Oct. 9, 2017.
- Determining yield monitoring system delay time with geostatistical and data segmentation approaches (<https://www.ars.usda.gov/ARSPUserFiles/50701000/cswq-0036-128359.pdf>) Jul. 2002, 13 pages.
- Precision Agriculture: Yield Monitors (dated Nov. 1998—metadata; last accessed Jul. 16, 2020) (<https://extensiondata.missouri.edu/pub/pdf/envqual/wq0451.pdf>) 4 pages.
- Paul et al., "Effect of soil water status and strength on trafficability" (1979) (<https://www.nrcresearchpress.com/doi/pdfplus/10.4141/cjss79-035>), 12 pages, Apr. 23, 1979.
- Sick, "Better understanding corn hybrid characteristics and properties can impact your seed decisions" (<https://emergence.fbn.com/agronomy/corn-hybrid-characteristics-and-properties-impact-seed-decisions>) By Steve Sick, FBN Breeding Project Lead | Sep. 21, 2018, 8 pages.
- Robertson et al., "Maize Stalk Lodging: Morphological Determinants of Stalk Strength" Mar. 2017, 10 pages.
- Martin, et al., "Breakage Susceptibility and Hardness of Corn Kernels of Various Sizes and Shapes", May 1987, 10 Pages.
- Martin et al., "Breakage Susceptibility and Harness of Corn Kernels of Various Sizes and Shapes," May 1987, 10 pages.
- Jones et al., "Brief history of agricultural systems modeling" Jun. 21, 2016, 15 pages.
- Dan Anderson, "Brief history of agricultural systems modeling" 1 pages. Aug. 13, 2019.
- A.Y. Şflek, "Determining the Physico-Mechanical Characteristics of Maize Stalks For Designing Harvester", *The Journal of Animal & Plant Sciences*, 27(3): 2017, p. 855-860 ISSN: 1018-7081, Jun. 1, 2017.
- Carmody, Paul, "Windrowing and harvesting", 8 pages Date: Feb. 3, 2010.
- Dabney, et al., "Forage Harvest Representation in RUSLE2", Published Nov. 15, 2013, 17 pages.
- John Deere S-Series Combines S760, S770, S780, S790 Brochure, 44 pages, Nov. 15, 2017.
- Sekhon et al., "Stalk Bending Strength is Strongly Associated with Maize Stalk Lodging Incidence Across Multiple Environments", Jun. 20, 2019, 23 pages.
- Thomison et al. "Abnormal Corn Ears", Apr. 28, 2015, 1 page.
- Anderson, "Adjust your Combine to Reduce Damage to High Moisture Corn", Aug. 13, 2019, 11 pages.
- Sumner et al., "Reducing Aflatoxin in Corn During Harvest and Storage", Reviewed by John Worley, Apr. 2017, 6 pages.
- Sick, "Better understanding corn hybrid characteristics and properties can impact your seed decisions", 8 pages, Sep. 21, 2018.
- TraCI/Change Vehicle State—Sumo Documentation, 10 pages, Retrieved Dec. 11, 2020.
- Arnold, et al., Chapter 8. "Plant Growth Component", Jul. 1995, 41 pages.

(56)

References Cited

OTHER PUBLICATIONS

- Humburg, Chapter: 37 "Combine Adjustments to Reduce Harvest Losses", 2019, South Dakota Board of Regents, 8 pages.
- Hoff, "Combine Adjustments", Cornell Extension Bulletin 591, Mar. 1943, 10 pages.
- University of Wisconsin, Corn Agronomy, Originally written Feb. 1, 2006 | Last updated Oct. 18, 2018, 2 pages.
- University of Nebraska-Lincoln, "Combine Adjustments for Downed Corn—Crop Watch", Oct. 27, 2017, 5 pages.
- "Combine Cleaning: Quick Guide to Removing Resistant Weed Seeds (Among Other Things)", Nov. 2006, 5 pages.
- Dekalb, "Corn Drydown Rates", 7 pages, Aug. 4, 2020.
- Mahmoud et al. Iowa State University, "Corn Ear Orientation Effects on Mechanical Damage and Forces on Concave", 1975, 6 pages.
- Sindelar et al., Kansas State University, "Corn Growth & Development" Jul. 17, 2017, 9 pages.
- Pannar, "Manage the Growth Stages of the Maize Plant With Pannar", Nov. 14, 2016, 7 pages.
- He et al., "Crop residue harvest impacts wind erodibility and simulated soil loss in the Central Great Plains", Sep. 27, 2017, 14 pages.
- Blanken, "Designing a Living Snow Fence for Snow Drift Control", Jan. 17, 2018, 9 pages.
- Jean, "Drones give aerial boost to ag producers", Mar. 21, 2019, 4 pages.
- Zhao et al., "Dynamics modeling for sugarcane sucrose estimation using time series satellite imagery", Jul. 27, 2017, 11 pages.
- Brady, "Effects of Cropland Conservation Practices on Fish and Wildlife Habitat", Sep. 1, 2007, 15 pages.
- Jasa, et al., "Equipment Adjustments for Harvesting Soybeans at 13%-15% Moisture", Sep. 15, 2017, 2 pages.
- Bendig et al., "Estimating Biomass of Barley Using Crop Surface Models (CSMs) Derived from UAV-Based RGB Imaging", Oct. 21, 2014, 18 pages.
- Robertson et al., "Maize Stalk Lodging: Morphological Determinants of Stalk Strength", Mar. 3, 2017, 10 pages.
- MacGowan et al. Purdue University, Corn and Soybean Crop Depredation by Wildlife, Jun. 2006, 14 pages.
- Martinez-Feria et al., Iowa State University, "Corn Grain Dry Down in Field From Maturity to Harvest", Sep. 20, 2017, 3 pages.
- Wrona, "Precision Agriculture's Value" Cotton Physiology Today, vol. 9, No. 2, 1998, 8 pages.
- Zhang et al., "Design of an Optical Weed Sensor Using Plant Spectral Characteristics" Sep. 2000, 12 pages.
- Hunt, et al., "What Weeds Can Be Remotely Sensed?", 5 pages, May 2016.
- Pepper, "Does an Adaptive Gearbox Really Learn How You Drive?", Oct. 30, 2019, 8 pages.
- Eggerl, "Optimization of Combine Processes Using Expert Knowledge and Methods of Artificial Intelligence", Oct. 7, 1982, 143 pages.
- Sheely et al., "Image-Based, Variable Rate Plant Growth Regulator Application in Cotton at Sheely Farms in California", Jan. 6-10, 2003 Beltwide Cotton Conferences, Nashville, TN, 17 pages.
- Kovacs et al., "Physical characteristics and mechanical behaviour of maize stalks for machine development", Apr. 23, 2019, 1-pages.
- Anonymous, "Optimizing Crop Profit Across Multiple Grain Attributes and Stover", ip.com, May 26, 2009, 17 pages.
- Breen, "Plant Identification: Examining Leaves", Oregon State University, 2020, 8 pages.
- Caglayan et al., A Plant Recognition Approach Using Shape and Color Features in Leaf Images, Sep. 2013, 11 pages.
- Casady et al., "Precision Agriculture" Yield Monitors University of Missouri-System, 4 pages, 1998.
- Apan et al., "Predicting Grain Protein Content in Wheat Using Hyperspectral Sensing of In-season Crop Canopies and Partial Least Squares Regression", 18 pages. 2006.
- Xu et al., "Prediction of Wheat Grain Protein by Coupling Multisource Remote Sensing Imagery and ECMWF Data", Apr. 24, 2020, 21 pages.
- Day, "Probability Distributions of Field Crop Yields," American Journal of Agricultural Economics, vol. 47, Issue 3, Aug. 1965, Abstract Only, 1 page.
- Butzen, "Reducing Harvest Losses in Soybeans", Pioneer, Jul. 23, 2020, 3 pages.
- Martin et al., "Relationship between secondary variables and soybean oil and protein concentration", Abstract Only, 1 page., 2007.
- Torres, "Precision Planting of Maize" Dec. 2012, 123 pages.
- Apan et al., "Predictive Mapping of Blackberry in the Condamine Catchment Using Logistic Regression and Spatial Analysis", Jan. 2008, 12 pages.
- Robson, "Remote Sensing Applications for the Determination of Yield, Maturity and Aflatoxin Contamination in Peanut", Oct. 2007, 275 pages.
- Bhattarai et al., "Remote Sensing Data to Detect Hessian Fly Infestation in Commercial Wheat Fields", Apr. 16, 2019, 8 pages.
- Towery, et al., "Remote Sensing of Crop Hail Damage", Jul. 21, 1975, 31 pages.
- Sa et al., "WeedMap: A Large-Scale Semantic Weed Mapping Framework Using Aerial Multispectral Imaging and Deep Neural Network for Precision Farming", Sep. 7, 2018, 25 pages.
- Mathyam et al., "Remote Sensing of Biotic Stress in Crop Plants and Its Applications for Pest Management", Dec. 2011, 30 pages.
- Martinez-Feria et al., "Evaluating Maize and Soybean Grain Dry-Down in the Field With Predictive Algorithms and Genotype-by-Environmental Analysis", May 9, 2019, 13 pages.
- "GIS Maps for Agriculture", Precision Agricultural Mapping, Retrieved Dec. 11, 2020, 6 pages.
- Paul, "Scabby Wheat Grain? Increasing Your Fan Speed May Help", <https://agcrops.osu.edu/newsletter/corn-newsletter/2015-20/scabby-wheat-grain-increasing-yourfan-speed-may-help>, C.O.R.N. Newsletter//2015-20, 3 pages.
- Clay et al., "Scouting for Weeds", SSMG-15, 4 pages, 2002.
- Taylor et al., "Sensor-Based Variable Rate Application for Cotton", 8 pages, 2010.
- Christiansen et al., "Designing and Testing a UAV Mapping System for Agricultural Field Surveying", Nov. 23, 2017, 19 pages.
- Haung et al., "Accurate Weed Mapping and Prescription Map Generation Based on Fully Convolutional Networks Using UAV Imagery", Oct. 1, 2018, 12 pages.
- Morrison, "Should You Use Tillage to Control Resistant Weeds", Aug. 29, 2014, 9 pages.
- Morrison, "Snow Trapping Snags Water", Oct. 13, 2005, 3 pages.
- "Soil Zone Index", <https://www.satimagingcorp.com/applications/natural-resources/agriculture> . . . , Retrieved Dec. 11, 2020, 5 pages.
- Malvic, "Soybean Cyst Nematode", University of Minnesota Extension, Oct. 19, 2020, 3 pages.
- Unglesbee, "Soybean Pod Shatter - Bad Enough to Scout Before Harvest? - Dtn", Oct. 17, 2018, 4 pp.
- Tao, "Standing Crop Residue Can Reduce Snow Drifting and Increase Soil Moisture", 2 pages, last accessed Jul. 14, 2020.
- Berglund, et al., "Swathing and Harvesting Canola", Jul. 2019, 8 pages.
- Bell et al., "Synthetic Aperture Radar and Optical Remote Sensing of Crop Damage Attributed to Severe Weather in the Central United States", Jul. 25, 2018, 1 page.
- Rosencrance, "Tabletop Grapes in India to Be Picked by Virginia Tech Robots", Jul. 23, 2020, 8 pages.
- Lofton, et al., The Potential of Grazing Grain Sorghum Residue Following Harvest, May 13, 2020, 11 pages.
- Beal et al., "Time Shift Evaluation to Improve Yield Map Quality", Published in Applied Engineering in Agriculture vol. 17(3): 385-390 (© 2001 American Society of Agricultural Engineers), 9 pages.
- "Tips and Tricks of Harvesting High Moisture Grain", <https://www.koenigequipment.com/blog/tips-and-tricks-of-harvesting-highmoisture-grain>, 7 pages, last accessed Jul. 14, 2020.
- Ransom, "Tips for Planting Winter Wheat and Winter Rye (for Grain) (Aug. 15, 2019)", 2017, 3 pages.

(56)

References Cited

OTHER PUBLICATIONS

- AgroWatch Tree Grading Maps, “The Grading Maps and Plant Count Reports”, <https://www.satimagingcorp.com/applications/natural-resources/agriculture/>, Retrieved Dec. 11, 2020, 4 pages.
- Ackley, “Troubleshooting Abnormal Corn Ears”, Jul. 23, 2020, 25 pages.
- Smith, “Understanding Ear Flex”, Feb. 25, 2019, 17 pages.
- Carroll et al., “Use of Spectral Vegetation Indices Derived from Airborne Hyperspectral Imagery for Detection of European Corn Borer Infestation in Iowa Corn Plots”, Nov. 2008, 11 pages.
- Agriculture, “Using drones in agriculture and capturing actionable data”, Retrieved Dec. 11, 2020, 18 pages.
- Bentley et al., “Using Landsat to Identify Thunderstorm Damage in Agricultural Regions”, Aug. 28, 2001, 14 pages.
- Duane Grant and the Idaho Wheat Commission, “Using Remote Sensing to Manage Wheat Grain Protein”, Jan. 2, 2003, 13 pages.
- Zhang et al., “Using satellite multispectral imagery for damage mapping of armyworm (*Spodoptera frugiperda*) in maize at a regional scale”, Apr. 10, 2015, 14 pages.
- Booker, “Video: Canadian cage mill teams up with JD”, Dec. 19, 2019, 6 pages.
- AgTalk Home, “Best Combine to Handle Weeds”, Posted Nov. 23, 2018, 9 pages.
- “Volunteer corn can be costly for soybeans”, Jun. 2, 2016, 1 page.
- Pflanz, et al., “Weed Mapping with UAS Imagery and a Bag of Visual Words Based Image Classifier”, Published Sep. 24, 2018, 17 pages.
- Hartzler, “Weed seed predation in agricultural fields”, 9 pages, 2009.
- Sa et al., “Weedmap: A Large-Scale Sematnic Weed Mapping Framework Using Aerial Multispectral Imaging and Deep Neural Netowrk for Precision Farming”, Sep. 6, 2018, 25 pages.
- Nagelkirk, Michigan State University-Extension, “Wheat Harvest: Minimizing the Risk of Fusarium Head Scab Losses”, Jul. 11, 2013, 4 pages.
- Saskatchewan, “Wheat: Winter Wheat”, (<https://www.saskatchewan.ca/business/agriculture-natural-resources-and-industry/agribusiness-farmers-and-ranchers/crops-and-irrigation/field-crops/cereals-barley-wheat-oats-triticale/wheat-winter-wheat>) 5 pages, last accessed Jul. 14, 2020.
- Quora, “Why would I ever use sport mode in my automatic transmission car? Will this increase fuel efficiency or isit simply a feature that makes form more fun when driving?”, Aug. 10, 2020, 5 pages.
- Wade, “Using a Drone’s Surface Model to Estimate Crop Yields & Assess Plant Health”, Oct. 19, 2015, 14 pages.
- Mathyam et al., “Remote Sensing of Biotic Stress in Crop Plants and Its Applications for Pest Stress”, Dec. 2011, 30 pages.
- “Four Helpful Weed-Management Tips for Harvest Time”, 2 pages, Sep. 4, 2019.
- Franz et al., “The role of topography, soil, and remotely sensed vegetation condition towards predicting crop yield”, University of Nebraska—Lincoln, Mar. 23, 2020, 44 pages.
- Peiffer et al., The Genetic Architecture of Maize Stalk Strength:, Jun. 20, 2013, 14 pages.
- Prosecution History for U.S. Appl. No. 16/380,691 including: Notice of Allowance dated Mar. 10, 2021 and Application and Drawings filed Apr. 10, 2019, 46 pages.
- U.S. Appl. No. 16/831,216 Application and Drawings filed Mar. 26, 2020, 56 pages.
- Notice of Allowance for U.S. Appl. No. 16/380,531 dated Apr. 5, 2021, 5 pages.
- Application and Drawings for U.S. Appl. No. 17/067,383, filed Oct. 9, 2020, 61 pages.
- Lamsal et al. “Sugarcane Harvest Logistics in Brazil” Iowa Research Online, Sep. 11, 2013, 27 pages.
- Jensen, “Algorithms for Operational Planning of Agricultural Field Operations”, Mechanical Engineering Technical Report ME-TR-3, Nov. 9, 2012, 23 pages.
- Chauhan, “Remote Sensing of Crop Lodging”, Nov. 16, 2020, 16 pages.
- Notice of Allowance for U.S. Appl. No. 16/171,978 dated Mar. 31, 2021, 6 pages.
- 7 Combine Tweaks to Boost Speed (https://www.agriculture.com/machinery/harvest-equipment/7-combine-tweaks-to-boost-speed_203-ar33059) 8 pages, Aug. 19, 2018.
- Managing corn harvest this fall with variable corn conditions (<https://www.ocj.com/2019/10/managing-corn-harvest-this-fall-with-variable-corn-conditions/>), 4 pages, Oct. 10, 2019.
- Reducing Aflatoxin in Corn During Harvest and Storage (<https://extension.uga.edu/publications/detail.html?number=B1231&title=Reducing%20Aflatoxin%20in%20Corn%20During%20Harvest%20and%20Storage>), 9 pages, Published with Full Review on Apr 19, 2017.
- Variable Rate Applications to Optimize Inputs (<https://www.cotton.org/tech/physiology/cpt/miscpubs/upload/CPT-v9No2-98-REPOP.pdf>), 8 pages, Nov. 2, 1998.
- Robin Booker, Video: Canadian cage mill teams up with JD (<https://www.producer.com/2019/12/video-canadian-cage-mill-teams-up-with-jd/>), 6 pages, Dec. 19, 2019.
- Jarnevich, et al. “Forecasting Weed Distributions using Climate Data: A GIS Early Warning Tool”, Invasive Plant Science and Management, 11 pages, Jan. 20, 2017.
- Burks, “Classification of Weed Species Using Color Texture Features and Discriminant Analysis” (<http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.468.5833&rep=rep1&type=pdf>), 8 pages, 2000.
- John Deere, <https://www.youtube.com/watch?v=1Gq77CfdGI4&list=PL1KGsSJ4CVV4rShNb3-sTMOiL8meHBL5> (last accessed Jul. 14, 2020), Jun. 15, 2020, 5 pages.
- Combine Adjustments (<http://corn.agronomy.wisc.edu/Management/L036.aspx>), 2 pages, Originally written Feb. 1, 2006; last updated Oct. 18, 2018.
- Ardekani, “Off- and on-ground GPR techniques for field-scale soil moisture mapping” Jun. 2013, 13 pages.
- Does an Adaptive Gearbox Really Learn How You Drive? (<https://practicalmotoring.com.au/voices/does-an-adaptive-gearbox-really-learn-how-you-drive/>), Oct. 30, 2019, 8 pages.
- https://www.researchgate.net/publication/222527694_Energy_Requirement_Model_for_a_Combine_Harvester_Part_I_Development_of_Component_Models, Abstract Only, Jan. 2005.
- <http://canola.okstate.edu/cropproduction/harvesting>, 8 pages, Aug. 2011.
- “Tips and Tricks of Harvesting High Moisture Grain”, <https://www.koenigequipment.com/blog/tips-and-tricks-of-harvesting-highmoisture-grain>, 5 pages, last accessed Feb. 11, 2021.
- Hoff, Combine Adjustements, Mar. 1943, 8 pages.
- Haung et al., “Accurate Weed Mapping and Prescription Map Generation Based onFully Convolutional Networks Using UAV Imagery”, 14 pages, Oct. 1, 2018.
- Thompson, “Morning glory can make it impossible to harvest corn”, Feb. 19, 2015, 4 pages.
- Content of European Office Action issued in European Application No. 19203883.4, dated May 3, 2021 (4 pages).
- Extended European Search Report and Written Opinion issued in European Patent Application No. 20208171.7, dated May 11, 2021, in 05 pages.
- Cordoba, M.A., Bruno, C.I. Costa, J.L. Peralta, N.R. and Balzarini, M.G., 2016, Protocol for multivariate homogenous zone delineation in precision agriculture, biosystems engineering, 143, pp. 95-107.
- Pioneer Estimator, “Com Yield Estimator” accessed on Feb. 13, 2018, 1 page. retrieved from: <https://www.pioneer.com/home/site/us/tools-apps/growing-tools/com-yield-estimator/>.
- Guindin, N. “Estimating Maize Grain Yield from Crop Biophysical Parameters Using Remote Sensing”, Nov. 4, 2013, 19 pages.
- EP Application No. 19203883.4-1004 Office Action dated May 3, 2021, 4 pages.
- Iowa State University Extension and Outreach, “Harvest Weed Seed Control”, Dec. 13, 2018, 6 pages. <https://crops.extension.iastate.edu/blog/bob-hartzler/harvest-weed-seed-control>.
- Getting Rid of WeedsThrough Integrated Weed Management, accessed on Jun. 25, 2021, 10 pages. <https://integratedweedmanagement.org/index.php/iwm-toolbox/the-harrington-seed-destroyer>.

(56)

References Cited

OTHER PUBLICATIONS

The Importance of Reducing Weed Seeds, Jul. 2018, 2 pages.
https://www.aphis.usda.gov/plant_health/soybeans/soybean-handouts.pdf.

Alternative Crop Guide, Published by the Jefferson Institute, "Buck-wheat", Revised Jul. 2002. 4 pages.

* cited by examiner

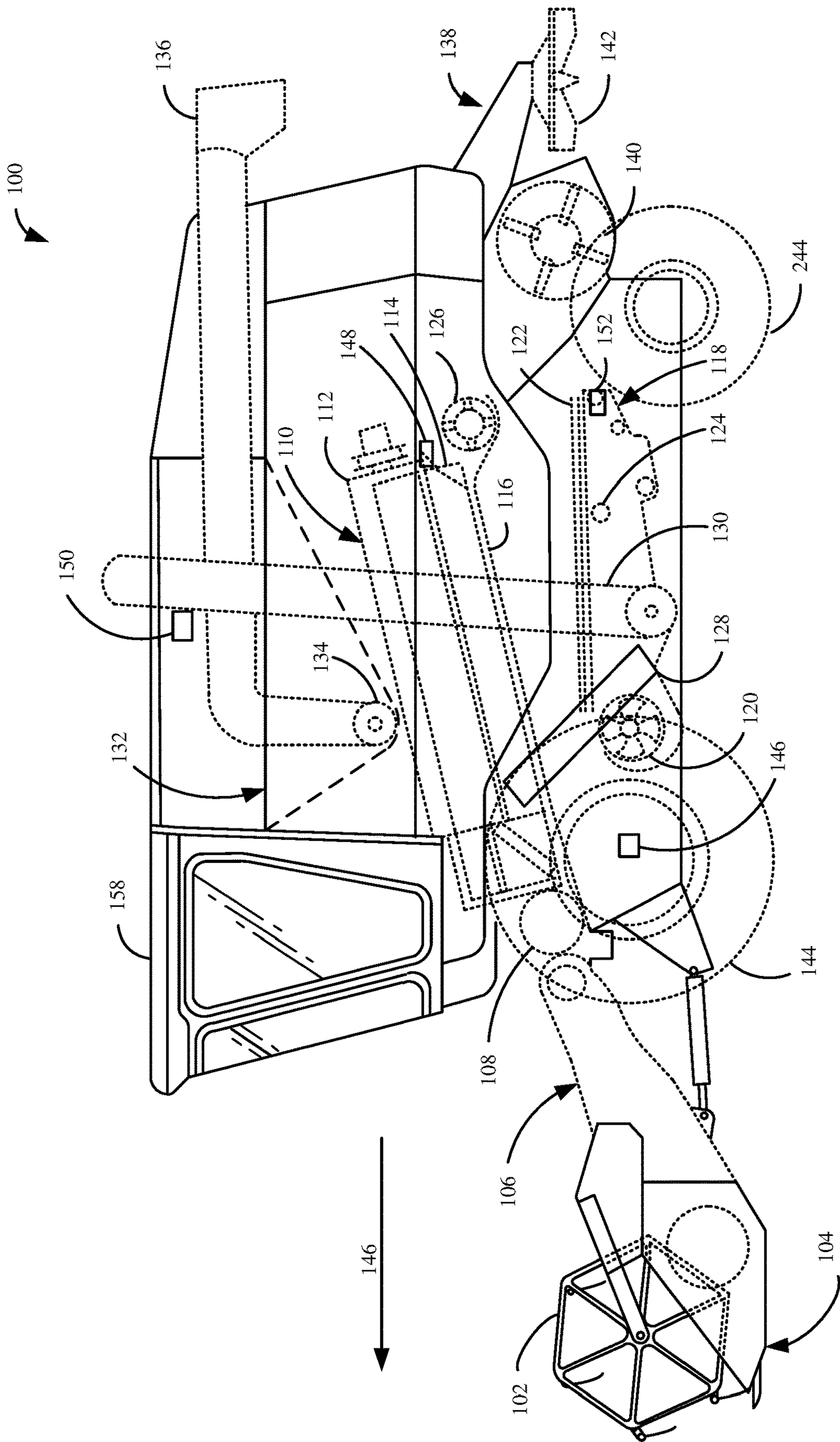


FIG. 1

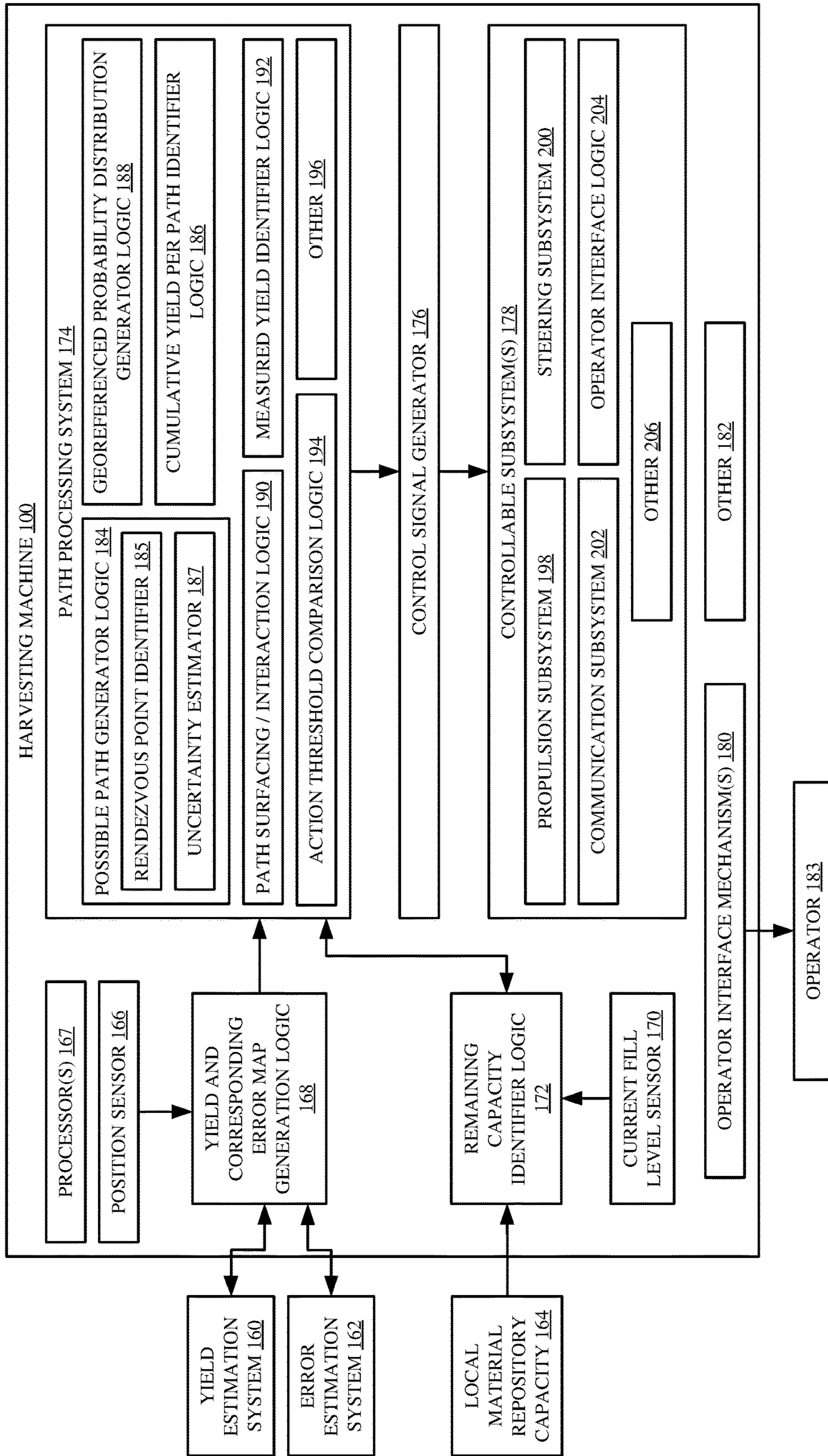


FIG. 2

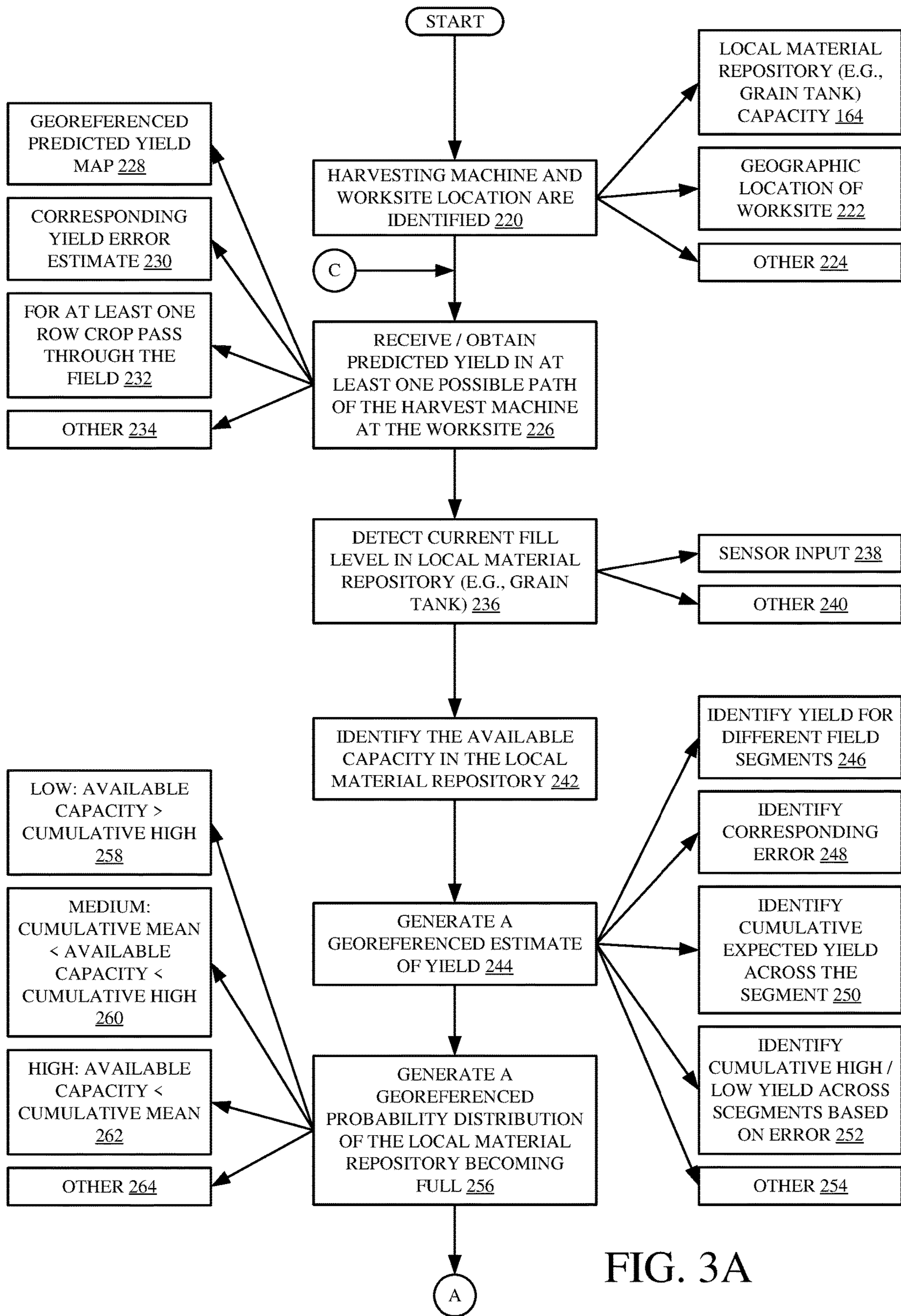


FIG. 3A

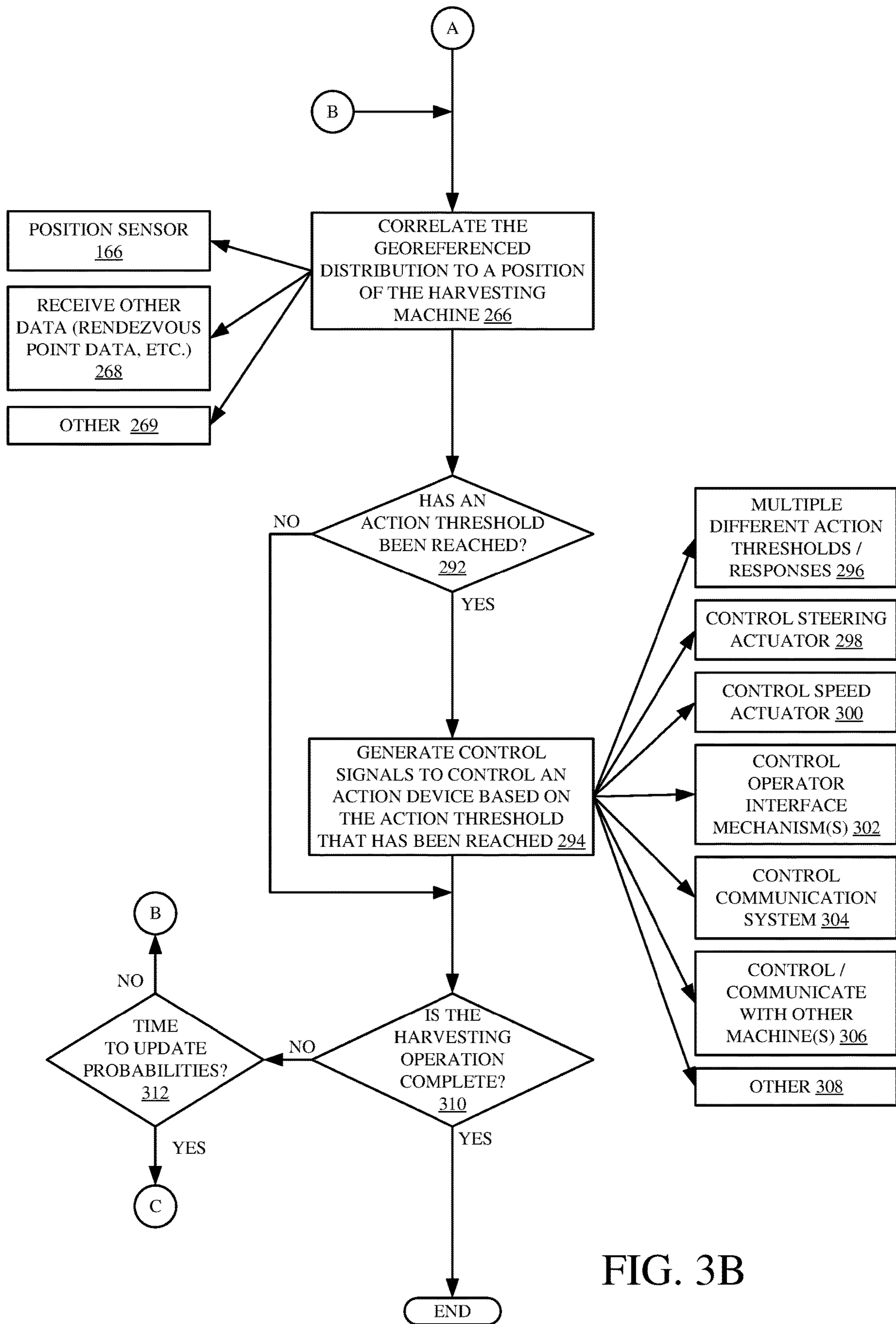


FIG. 3B

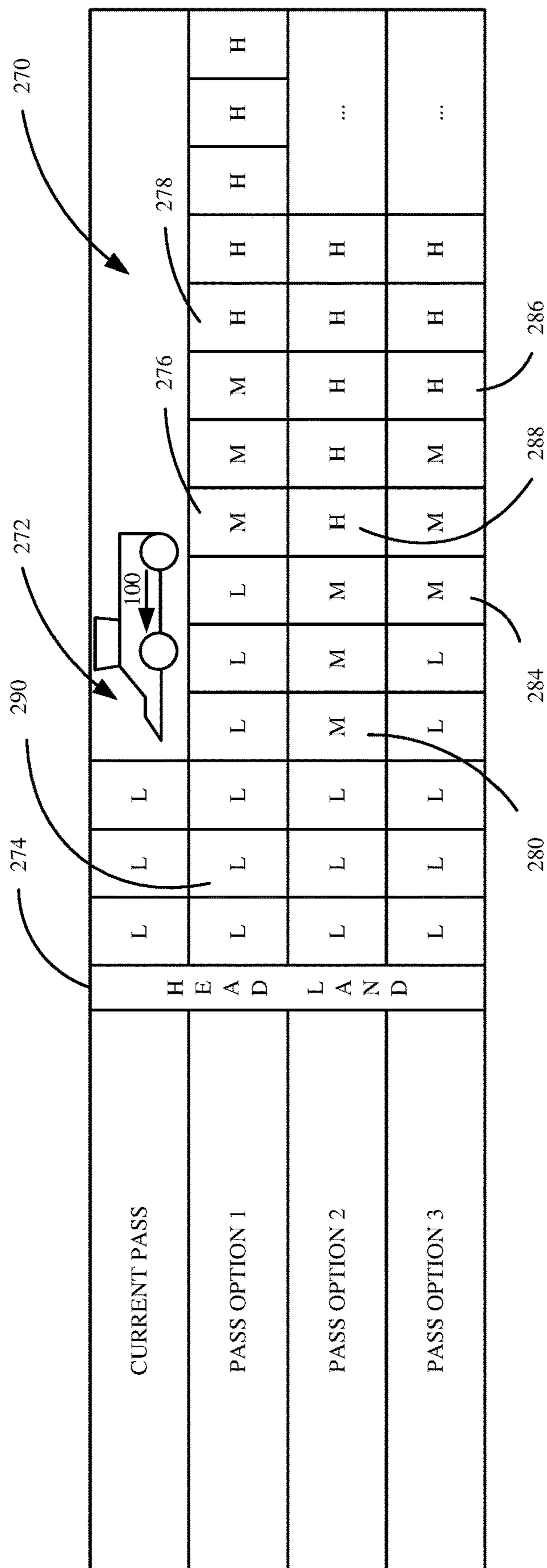


FIG. 3C

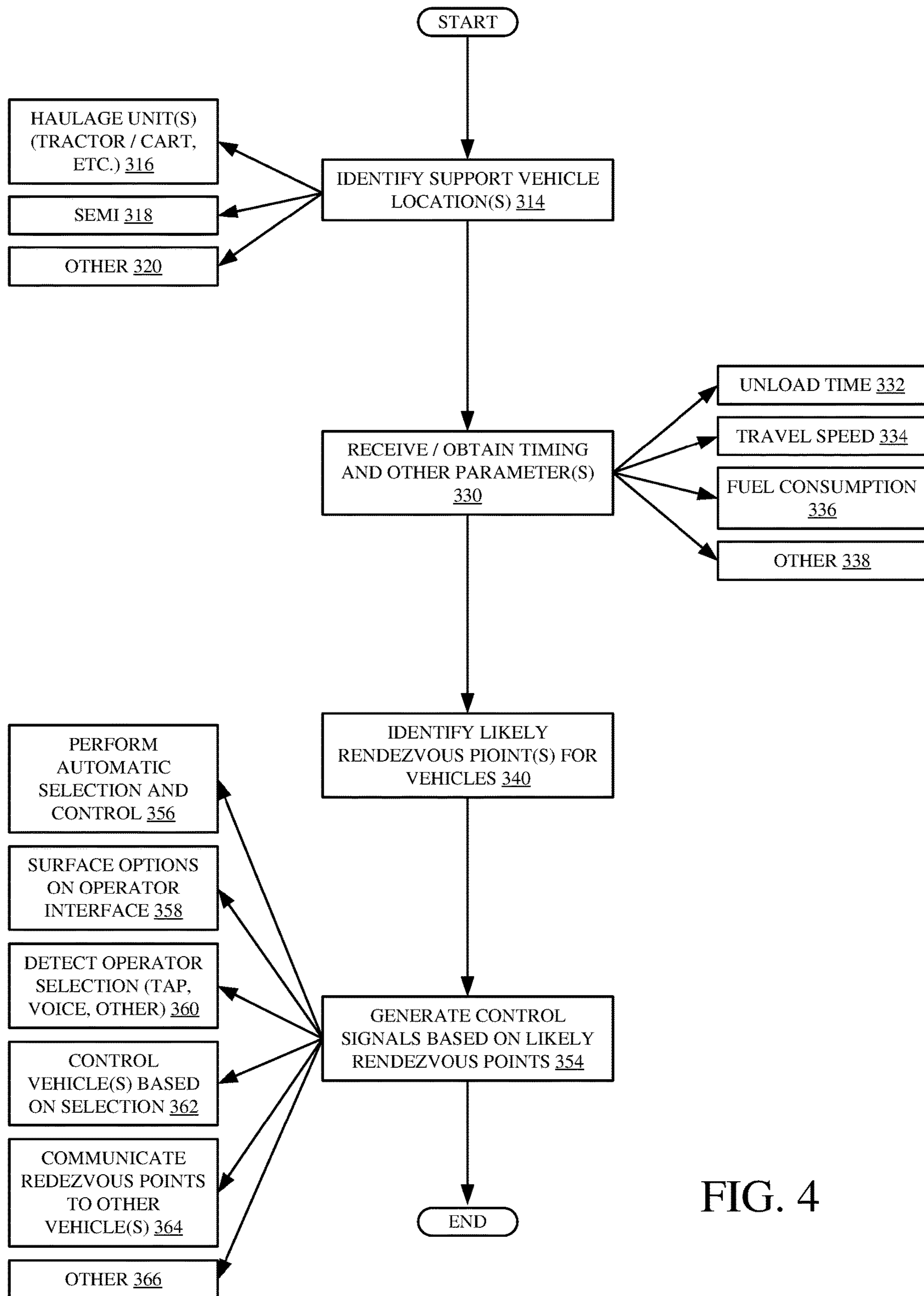


FIG. 4

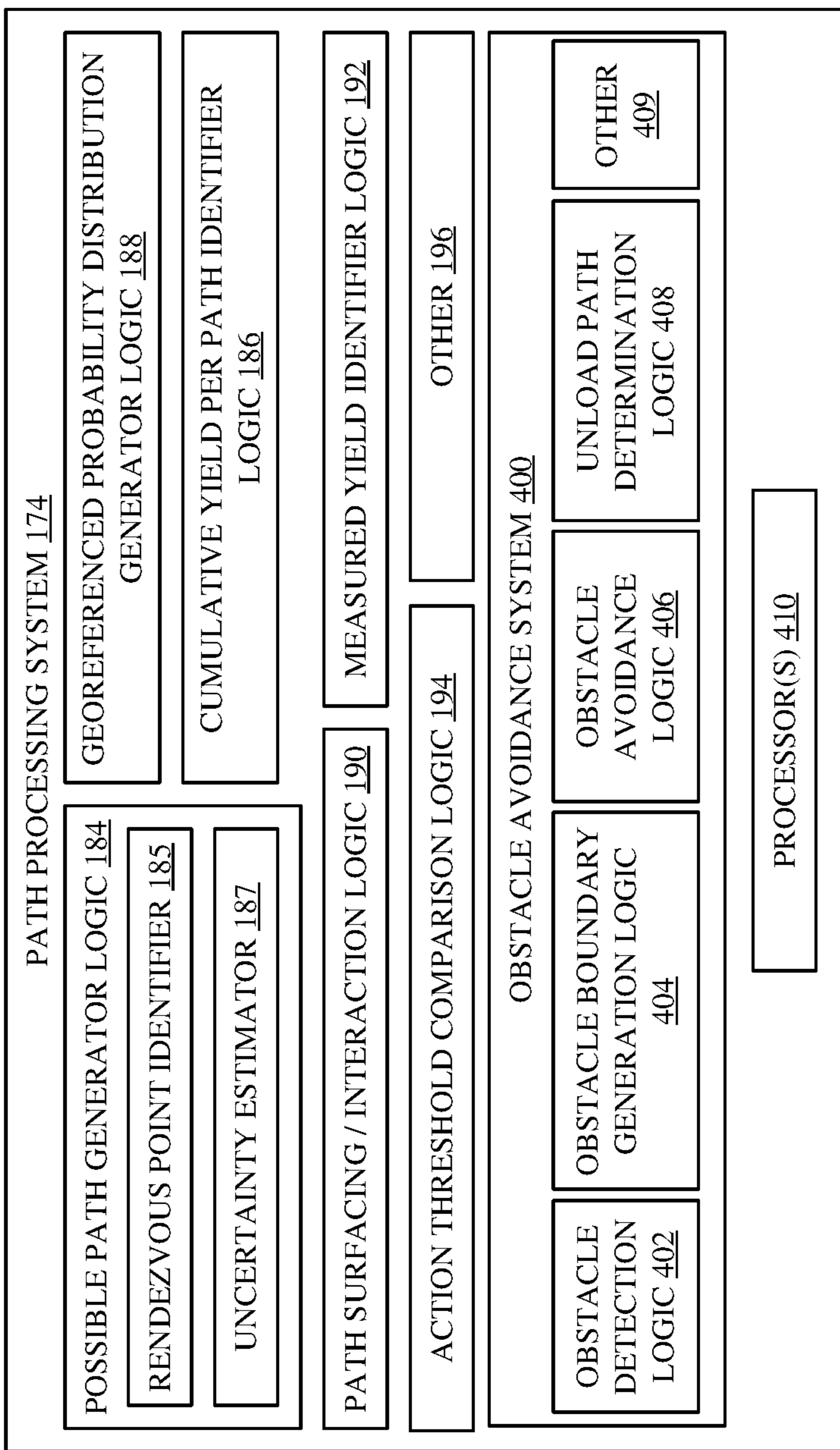


FIG. 5

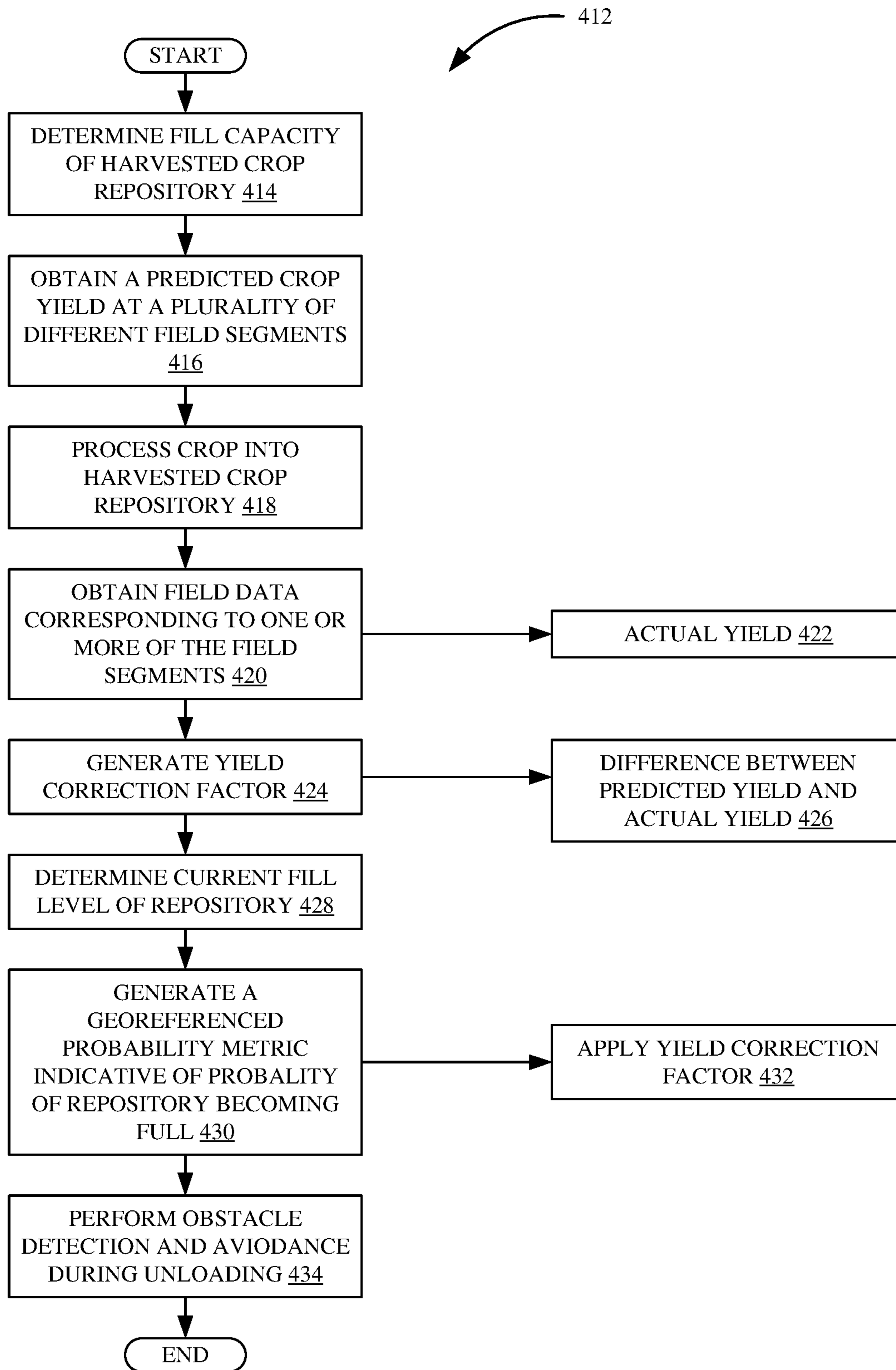


FIG. 6

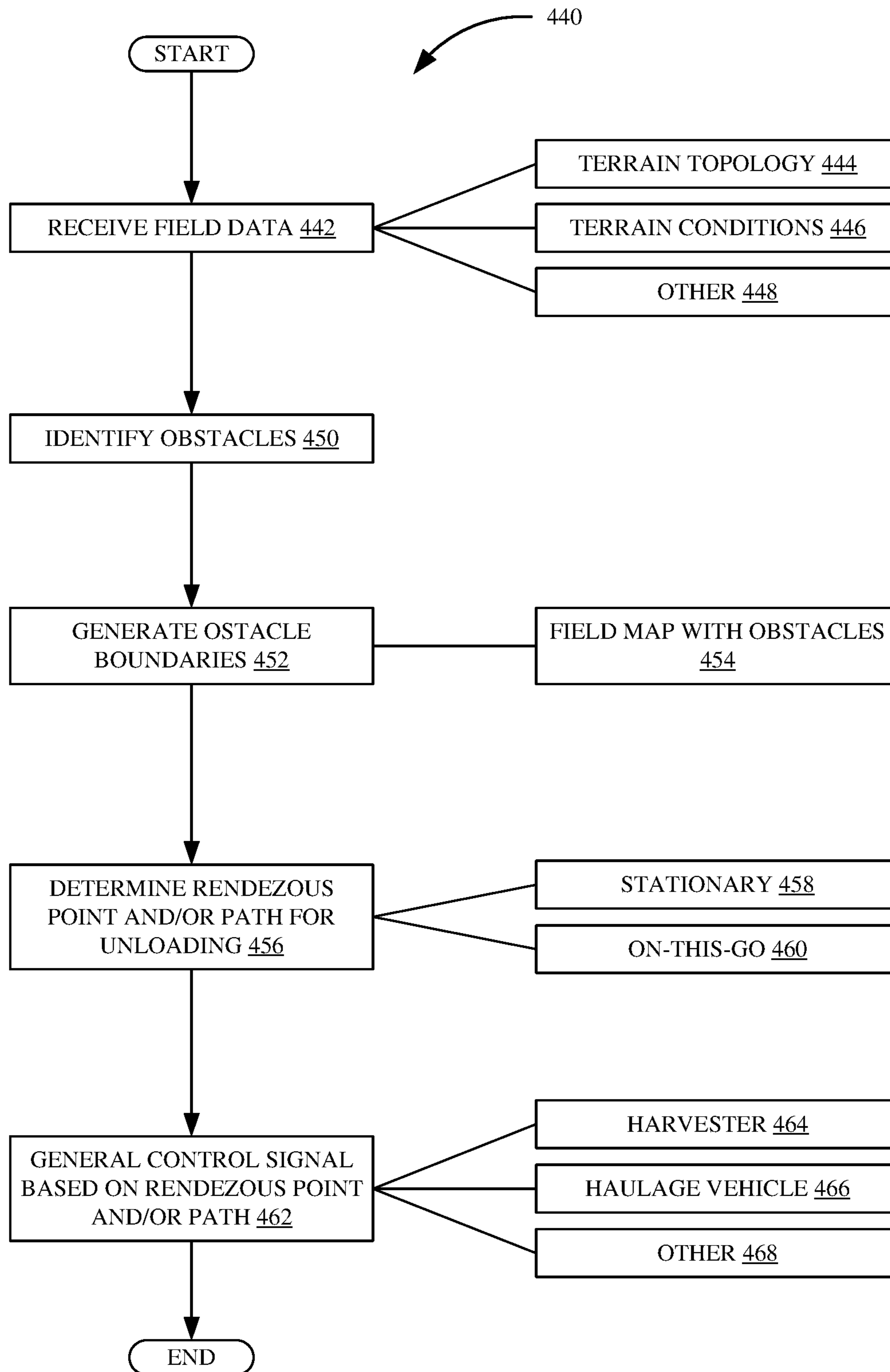


FIG. 7

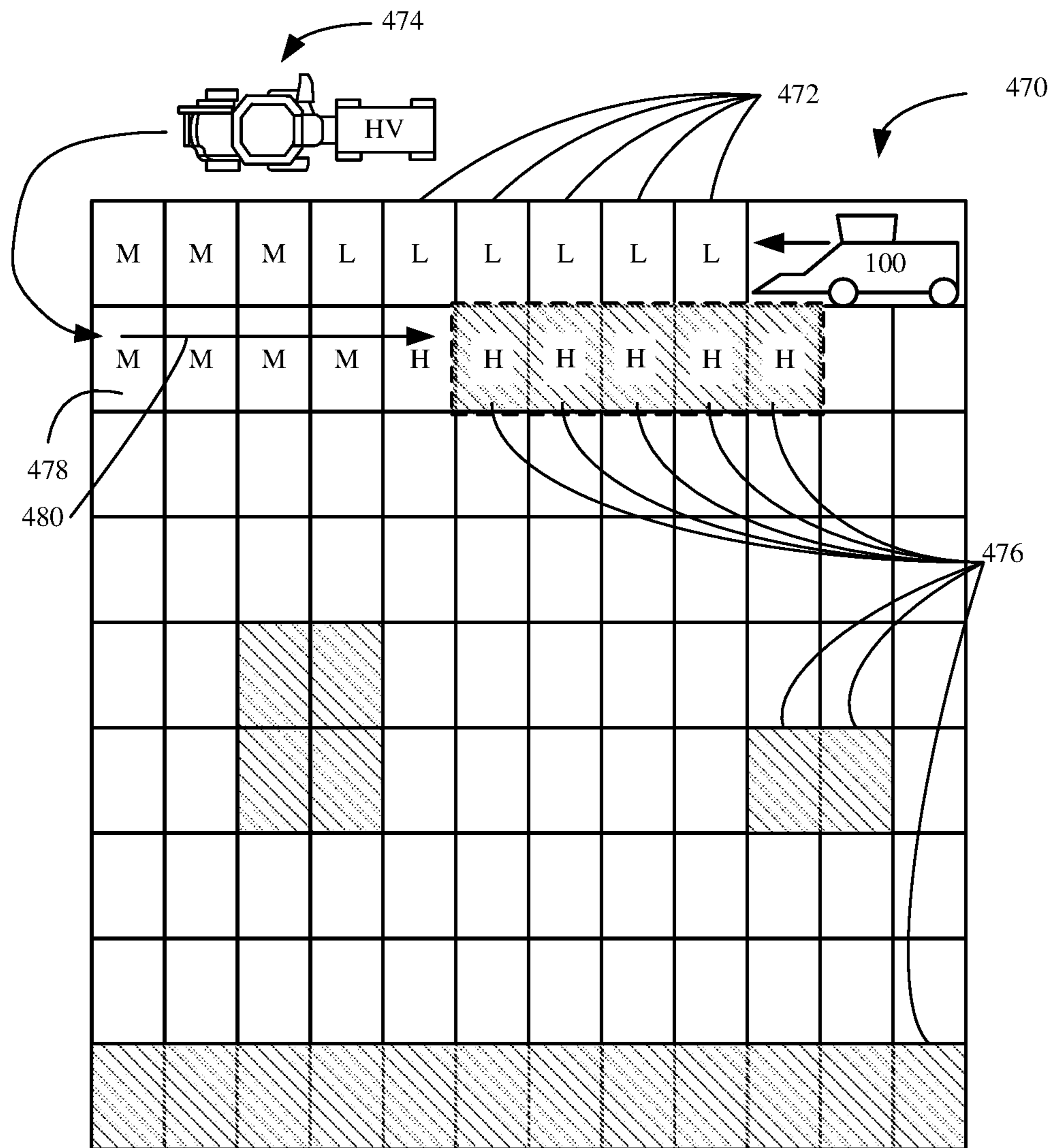


FIG. 8

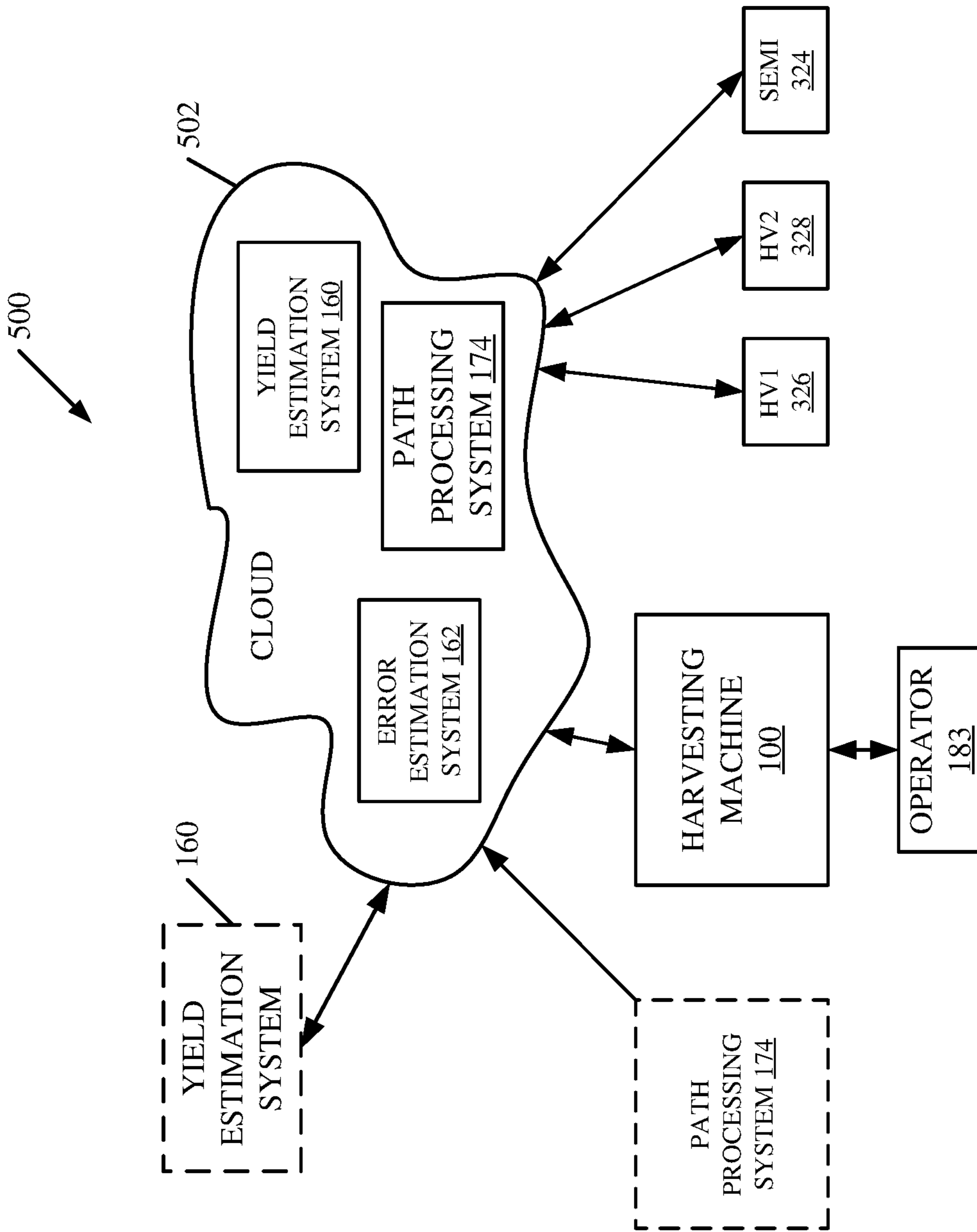


FIG. 9

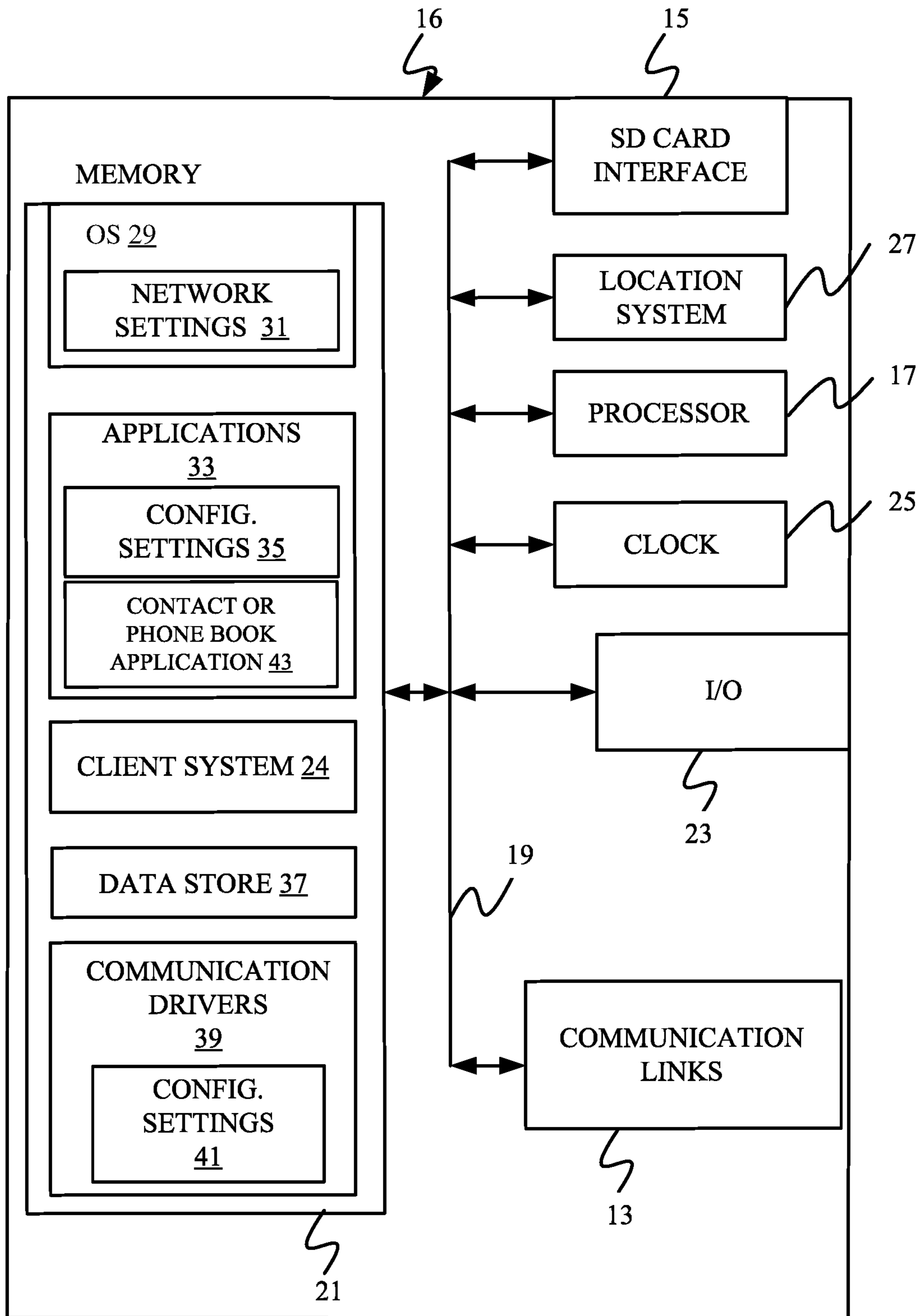


FIG. 10

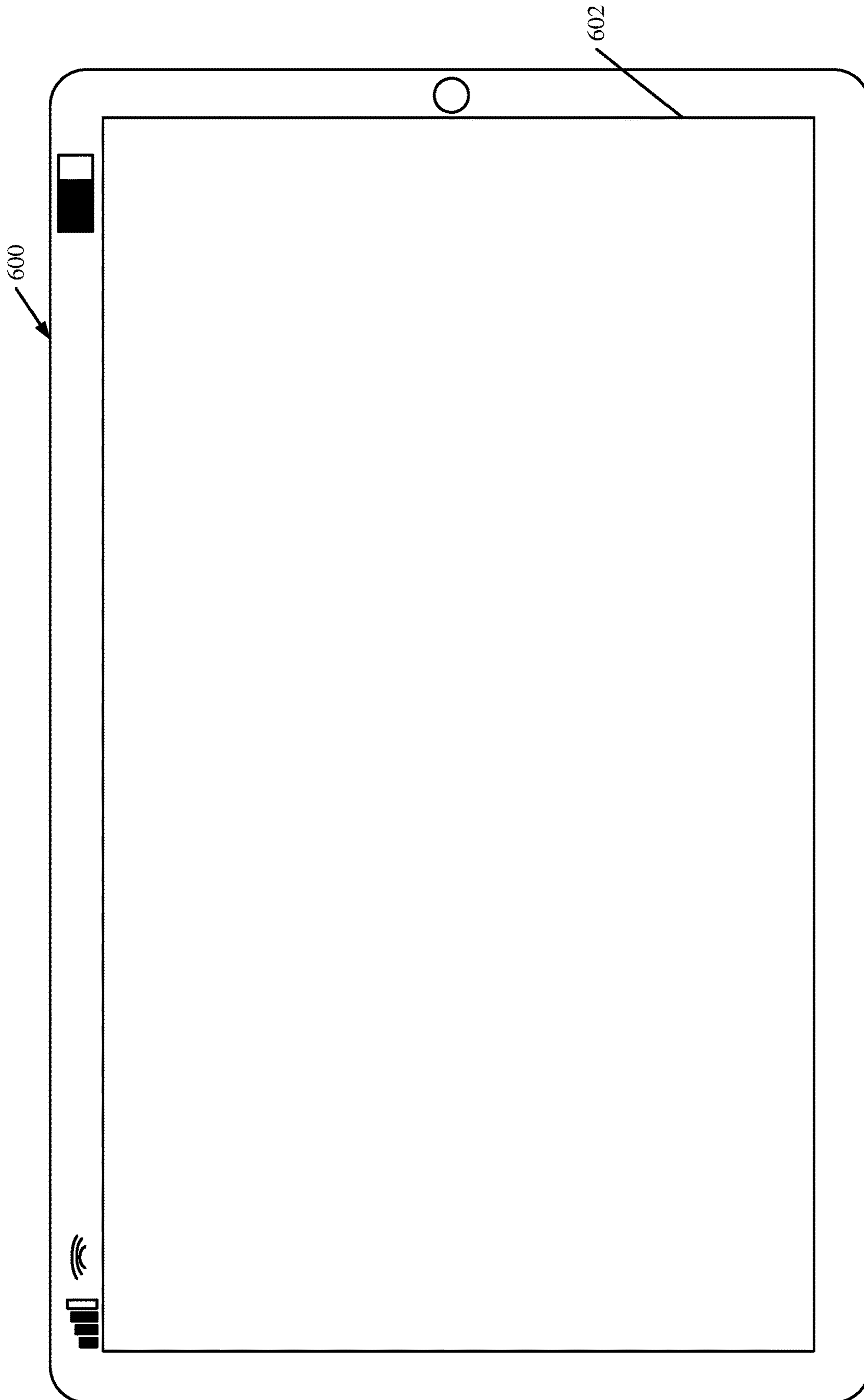


FIG. 11

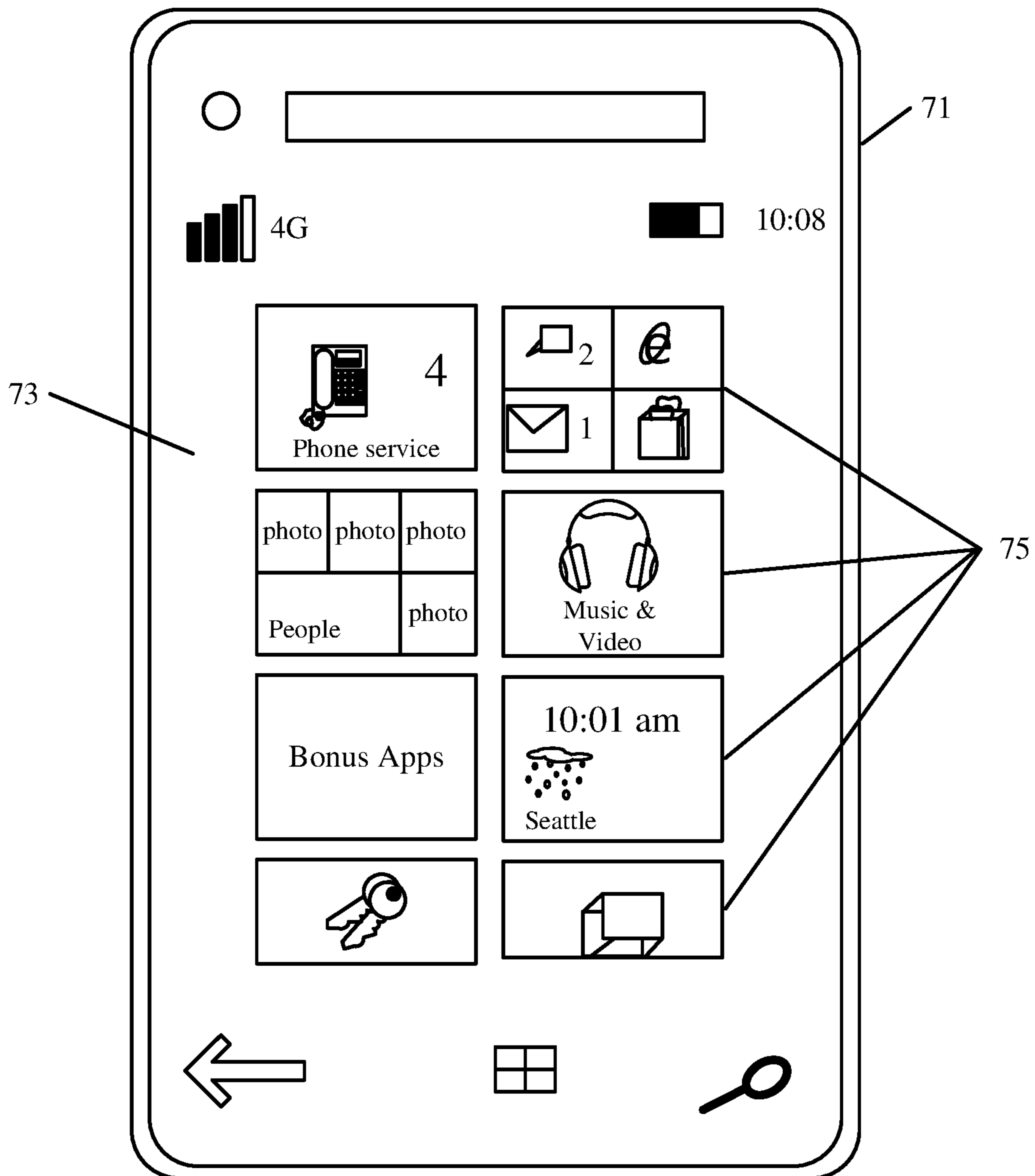


FIG. 12

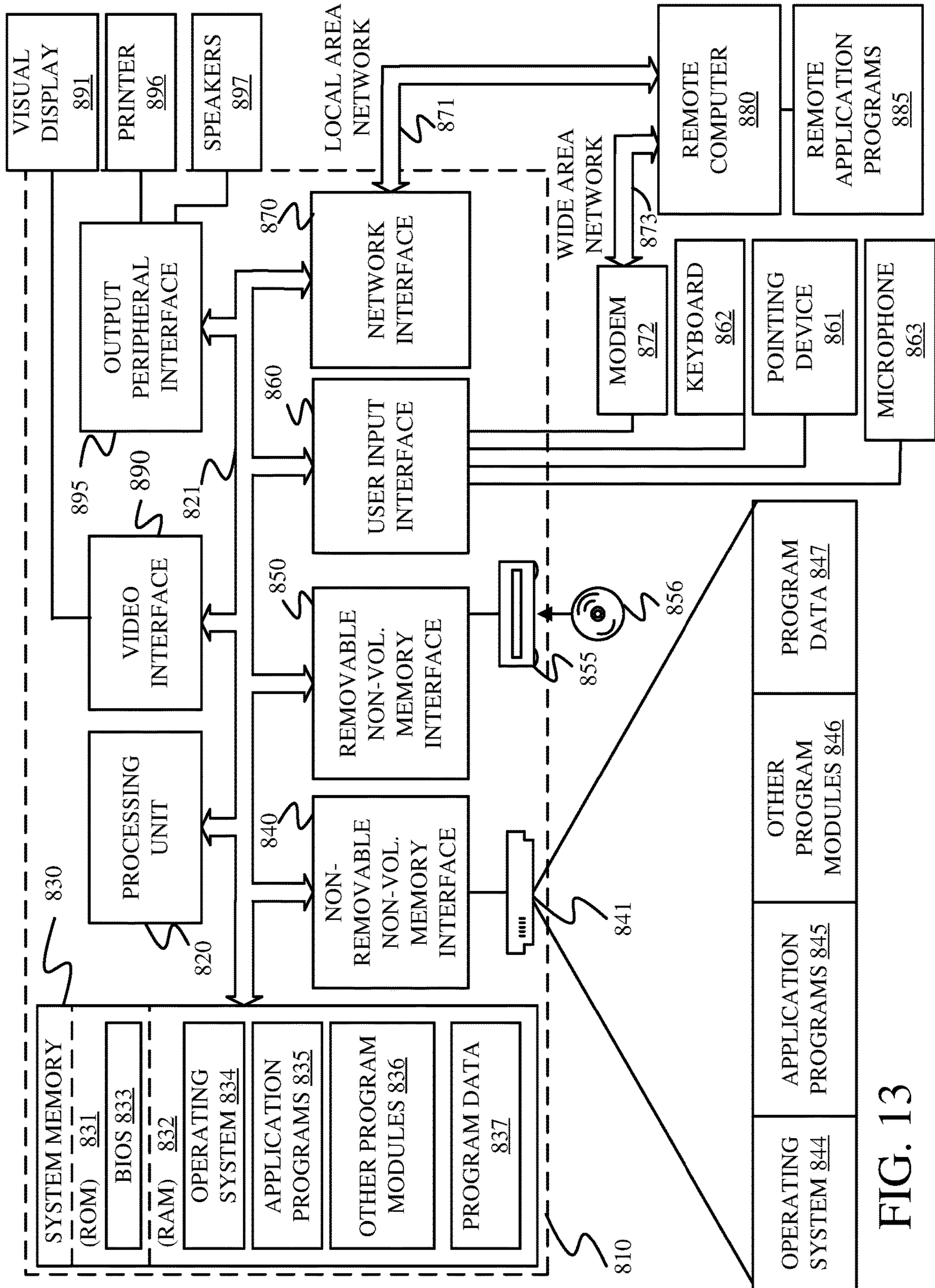


FIG. 13

**HARVESTING MACHINE CONTROL
SYSTEM WITH FILL LEVEL PROCESSING
BASED ON YIELD DATA**

CROSS-REFERENCE TO RELATED
APPLICATION

The present application is a continuation-in-part of and claims priority of U.S. patent application Ser. No. 16/171, 978, filed Oct. 26, 2018, the contents of which are hereby incorporated by reference in their entirety.

FIELD OF THE DESCRIPTION

The present description generally relates to a mobile harvesting machine. More specifically, but not by limitation, the present description relates to controlling a mobile harvesting machine based on fill level prediction using a priori and actual yield data.

BACKGROUND

There are many different types of mobile machines. There are also many different types of mobile machines that have local material storage repositories that store material that is gathered, or that is distributed, by the machine.

For instance, in one example, an agricultural harvester, such as a combine harvester, harvests material, such as grain. In harvesting grain, it processes the grain and stores it in a clean grain tank. When the clean grain tank is full, the combine harvester unloads the clean grain into a haulage unit, which may be a grain cart pulled by a tractor. The haulage unit then often transports the harvested grain to another vehicle, such as a semi-truck for transport to a different location.

Other examples of mobile work machines that collect material include machines such as a sugarcane harvester, a forage harvester, a baler, a timber harvester, an asphalt milling machine, a scraper, among a wide variety of other machines.

With these types of machines, logistical efficiency can be desirable. For instance, if a combine harvester reaches its full capacity at some point in a field, and there is no haulage unit nearby, then the combine harvester sits idle, waiting to unload its clean grain tank, until a haulage unit arrives. This increases the inefficiency of the combine harvester, and of the overall harvesting operation.

Similarly, in a given harvesting operation, there may be multiple different combine harvesters operating in a single field, along with multiple different haulage units. If the haulage units go to the wrong harvester (e.g., if they go to a harvester that is not yet at its full capacity, while a different harvester is already at its full capacity), this can also raise the inefficiency of the operation. Further, it may be that the operators of the haulage units do not know when a particular combine harvester is reaching its capacity.

Machines that distribute material often also have a local repository that stores the material to be distributed. Such agricultural machines include sprayers or other vehicles that apply fertilizer or other chemicals to a field. In operation, the sprayer is often loaded with fertilizer or another chemical and distributes it on a field. When the local storage repository (e.g., the tank) becomes empty, the sprayer or the other vehicle must have more fertilizer or chemical loaded into it.

The discussion above is merely provided for general background information and is not intended to be used as an aid in determining the scope of the claimed subject matter.

SUMMARY

An agricultural harvesting machine comprises a harvested crop repository having a fill capacity, a crop processing functionality configured to engage crop in a field, perform a crop processing operation on the crop, and move the processed crop to the harvested crop repository, and a fill level sensor configured to generate a fill level signal indicative of a current fill level of the harvested crop repository. A path processing system is configured to obtain a predicted crop yield at a plurality of different field segments along a harvester path on the field, obtain field data corresponding to one or more of the field segments, the field data being generated based on sensor data from a sensor on the agricultural harvesting machine as the agricultural harvesting machine is performing the crop processing operation, generate a yield correction factor based on the received field data and the predicted crop yield at the one or more field segments, based on applying the yield correction factor to the predicted crop yield, and generate a georeferenced probability metric indicative of a probability that the harvested crop repository will reach the fill capacity at a particular geographic location along the field. A control signal generator is configured to generate a control signal to control the agricultural harvesting machine based on the georeferenced probability metric.

This Summary is provided to introduce a selection of concepts in a simplified form that are further described below in the Detailed Description. This Summary is not intended to identify key features or essential features of the claimed subject matter, nor is it intended to be used as an aid in determining the scope of the claimed subject matter. The claimed subject matter is not limited to implementations that solve any or all disadvantages noted in the background.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. 1 is a partial pictorial, partial schematic view of one example of an agricultural harvesting machine (a combine harvester).

FIG. 2 is a block diagram showing one example of different portions of the harvesting machine illustrated in FIG. 1, in more detail.

FIGS. 3A and 3B (collectively referred to herein as FIG. 3) show a flow chart illustrating one example of the operation of a harvesting machine.

FIG. 3C is a pictorial illustration of one example of a user interface display.

FIG. 4 is a flow diagram illustrating one example of the operation of a path processing system in an agricultural harvesting machine.

FIG. 4A is a pictorial illustration showing one example of a user interface display.

FIG. 5 is a schematic diagram of one example of a path processing system.

FIG. 6 is a flow diagram illustrating one example of the operation of a path processing system in an agricultural harvesting machine.

FIG. 7 is a flow diagram illustrating one example of the operation of an obstacle avoidance system in an agricultural harvesting machine.

FIG. 8 is a schematic diagram of an example operation of an obstacle avoidance system in a field.

FIG. 9 is a block diagram showing one example of a harvesting machine deployed in a remote server environment.

FIGS. 10-12 show examples of mobile devices that can be used in the architectures shown in the previous figures.

FIG. 13 is a block diagram showing one example of a computing environment that can be used in the architectures shown in the previous figures.

DETAILED DESCRIPTION

With current combine harvesters, it can be difficult to tell when the clean grain tank is full. It can be even more difficult to predict, where, in the field that is being harvested, the clean grain tank will be full so that a haulage unit can rendezvous with the harvesting machine, at that point, or just prior to that point. Thus, it can be difficult to deploy harvesting machines and haulage units in an efficient manner. The present description thus proceeds with respect to a system in which a yield estimate is received for a field being harvested. The yield estimate can also include an error estimate indicative of a likely error in the yield estimate. The yield estimate and its corresponding error are used to generate a georeferenced probability distribution indicative of different locations where the grain tank on the harvester will likely be full. A control system generates control signals to control different portions of the harvester, based upon the georeferenced probability distribution. This greatly enhances the operation of the harvester, in that it reduces the time that the harvester may be idle and waiting to unload. In addition, the harvester can be automatically controlled to take a path, or to travel at a ground speed, based on a desired rendezvous point with a haulage unit.

The same types of operations can be performed with work other machines that collect material, such as other harvesters, asphalt milling machines, scrapers, etc. The same types of operations can also be performed with respect to machines that distribute material, such as fertilizer or chemical application equipment. In those machines, it can be difficult to know where on a worksite the tank will be empty and need to be refilled. It can also be difficult to know where to rendezvous with a haulage unit used to refill the tank.

These are just examples how of the present description can be applied, and additional examples are provided below, all of which are contemplated herein.

FIG. 1 is a partial pictorial, partial schematic, illustration of an agricultural machine 100, in an example where machine 100 is a combine harvester (also referred to as harvester or combine 100). It can be seen in FIG. 1 that combine 100 illustratively includes an operator compartment 101, which can have a variety of different operator interface mechanisms, for controlling combine 100. Combine 100 can include a set of front end equipment that can include header 102, and a cutter generally indicated at 104. It can also include a feeder house 106, a feed accelerator 108, and a thresher generally indicated at 110. Thresher 110 illustratively includes a threshing rotor 112 and a set of concaves 114. Further, combine 100 can include a separator 116 that includes a separator rotor. Combine 100 can include a cleaning subsystem (or cleaning shoe) 118 that, itself, can include a cleaning fan 120, chaffer 122 and sieve 124. The material handling subsystem in combine 100 can include (in addition to a feeder house 106 and feed accelerator 108) discharge beater 126, tailings elevator 128, clean grain elevator 130 (that moves clean grain into clean grain tank 132) as well as unloading auger 134 and spout 136. Combine 100 can further include a residue subsystem 138 that can include chopper 140 and spreader 142. Combine 100 can also have a propulsion subsystem that includes an engine that drives ground engaging wheels 144 or tracks, etc. It will

be noted that combine 100 may also have more than one of any of the subsystems mentioned above (such as left and right cleaning shoes, separators, etc.).

In operation, and by way of overview, combine 100 illustratively moves through a field in the direction indicated by arrow 146. As it moves, header 102 engages the crop to be harvested and gathers it toward cutter 104. After it is cut, it is moved through a conveyor in feeder house 106 toward feed accelerator 108, which accelerates the crop into thresher 110. The crop is threshed by rotor 112 rotating the crop against concaves 114. The threshed crop is moved by a separator rotor in separator 116 where some of the residue is moved by discharge beater 126 toward the residue subsystem 138. It can be chopped by residue chopper 140 and spread on the field by spreader 142. In other configurations, the residue is simply chopped and dropped in a windrow, instead of being chopped and spread.

Grain falls to cleaning shoe (or cleaning subsystem) 118. Chaffer 122 separates some of the larger material from the grain, and sieve 124 separates some of the finer material from the clean grain. Clean grain falls to an auger in clean grain elevator 130, which moves the clean grain upward and deposits it in clean grain tank 132. Residue can be removed from the cleaning shoe 118 by airflow generated by cleaning fan 120. Cleaning fan 120 directs air along an airflow path upwardly through the sieves and chaffers and the airflow carries residue can also be rearwardly in combine 100 toward the residue handling subsystem 138.

Tailings can be moved by tailings elevator 128 back to thresher 110 where they can be re-threshed. Alternatively, the tailings can also be passed to a separate re-threshing mechanism (also using a tailings elevator or another transport mechanism) where they can be re-threshed as well.

FIG. 1 also shows that, in one example, combine 100 can include ground speed sensor 147, one or more separator loss sensors 148, a clean grain camera 150, and one or more cleaning shoe loss sensors 152. Ground speed sensor 147 illustratively senses the travel speed of combine 100 over the ground. This can be done by sensing the speed of rotation of the wheels, the drive shaft, the axel, or other components. The travel speed can also be sensed by a positioning system, such as a global positioning system (GPS), a dead reckoning system, a LORAN system, or a wide variety of other systems or sensors that provide an indication of travel speed.

Cleaning shoe loss sensors 152 illustratively provide an output signal indicative of the quantity of grain loss by both the right and left sides of the cleaning shoe 118. In one example, sensors 152 are strike sensors which count grain strikes per unit of time (or per unit of distance traveled) to provide an indication of the cleaning shoe grain loss. The strike sensors for the right and left sides of the cleaning shoe can provide individual signals, or a combined or aggregated signal. It will be noted that sensors 152 can comprise only a single sensor as well, instead of separate sensors for each shoe.

Separator loss sensor 148 provides a signal indicative of grain loss in the left and right separators. The sensors associated with the left and right separators can provide separate grain loss signals or a combined or aggregate signal. This can be done using a wide variety of different types of sensors as well. It will be noted that separator loss sensors 148 may also comprise only a single sensor, instead of separate left and right sensors.

It will also be appreciated that sensor and measurement mechanisms (in addition to the sensors already described) can include other sensors on combine 100 as well. For instance, they can include a residue setting sensor that is

configured to sense whether machine **100** is configured to chop the residue, drop a windrow, etc. They can include cleaning shoe fan speed sensors that can be configured proximate fan **120** to sense the speed of the fan. They can include a threshing clearance sensor that senses clearance between the rotor **112** and concaves **114**. They include a threshing rotor speed sensor that senses a rotor speed of rotor **112**. They can include a chaffer clearance sensor that senses the size of openings in chaffer **122**. They can include a sieve clearance sensor that senses the size of openings in sieve **124**. They can include a material other than grain (MOG) moisture sensor that can be configured to sense the moisture level of the material other than grain that is passing through combine **100**. They can include machine setting sensors that are configured to sense the various configurable settings on combine **100**. They can also include a machine orientation sensor that can be any of a wide variety of different types of sensors that sense the orientation of combine **100**. Crop property sensors can sense a variety of different types of crop properties, such as crop type, crop moisture, and other crop properties. They can also be configured to sense characteristics of the crop as they are being processed by combine **100**. For instance, they can sense grain feed rate, as it travels through clean grain elevator **130**. They can sense mass flow rate of grain through elevator **130**, or provide other output signals indicative of other sensed variables. Some additional examples of the types of sensors that can be used are described below.

FIG. **2** is a block diagram showing one example of a portion of harvesting machine (or combine) **100**, in more detail. In the example shown in FIG. **2**, machine **100** is also shown receiving an input from yield estimation system **160**, and error estimation system **162**. It receives an input indicating the capacity of local material repository (e.g., the capacity of clean grain tank **132**). The capacity input is indicated by block **164** in the block diagram of FIG. **2**. It will be appreciated that systems **160** and **162**, and capacity indicator **164**, can all be on machine **100**. They are shown separately for the sake of example only.

Also, FIG. **2** shows that, in one example, machine **100** includes position sensor **166**, processor(s) **167**, yield and corresponding error map generation logic **168**, current fill level sensor **170**, remaining capacity identifier logic **172**, path processing system **174**, control signal generator **176**, controllable subsystems **178**, operator interface mechanisms **180**, and it can include a wide variety of other items **182**. Path processing system **174** illustratively includes possible path generator logic **184** (which can include rendezvous point identifier logic **185** and uncertainty estimator **187** and other items **189**), cumulative yield per path identifier logic **186**, georeferenced probability distribution generator logic **188**, path surfacing/interaction logic **190**, measured yield identifier logic **192**, action threshold comparison logic **194**, and it can include other items **196**. Controllable subsystems **178** can include propulsion subsystem **198**, steering subsystem **200**, communication subsystem **202**, operator interface logic **204**, and it can include other items **206**. The other items can include such things as the material handling subsystem, the cleaning subsystem, and the residue subsystem all discussed above with respect to FIG. **1**. Before describing the operation of harvesting machine **100** in more detail, a brief description of some of the items illustrated in FIG. **2**, and their operation, will first be provided.

Yield estimation system **160** illustratively generates an estimate of yield at different geographic locations in the field being harvested by machine **100**. The yield estimation system **160** can take a wide variety of different forms and

illustratively provides a georeferenced a priori estimate of yield. The estimating techniques can include a wide variety of different techniques such as in-season remote sensing, sampling ears from individual plants and extrapolating results across the field, and crop modeling. Yield estimation system **160** may include near real time sensing which may include, for instance, on-board image capture devices (which capture images ahead of machine **100**, or to the sides of machine **100**) and corresponding image processing logic that processes the images to identify an estimated yield. The on-board system may include other types of perception systems as well, such as LIDAR, stereo cameras, etc. In another example, yield estimation system **160** can include a system that receives aerial images that are processed to generate normalized different vegetative index (NDVI) or leaf area index (LAI) at a particular growth stage, and uses one or more of those indices to estimate harvested yield. Yield estimation system **160** can also include real time yield sensors, which sense the current yield (such as the mass flow rate of grain through machine **100**, or other sensors indicative of yield) and correct the forward-looking yield estimates in the field, and particularly in the path over which machine **100** is traveling. These and other types of yield estimation systems are contemplated herein.

Error estimation system **162** illustratively estimates an error corresponding to the yield estimate generated by system **160**. In some examples, the error may be assumed to be 0%. In other examples, the error may be georeferenced and based on factors such as sensor signals, model outputs, or other sources of information used to predict or estimate the yield. It may also be based on factors such as the time since a last ground-truthed data collection was performed, historical differences between predicted and measured yield for this location, environmental conditions or other factors which may result in a difference between the estimated yield provided by system **160** and the actual measured yield at a particular location.

Where statistical techniques are used by yield estimation system **160** in order to generate an estimated yield value, then estimated error distributions may be determined along with the expected yield values. Where perception systems are used by yield estimation system **160**, then error may be estimated based on historic differences between the estimated and measured yields. The history may be from prior harvest at this or other locations, from the current harvesting operation or a combination of the two data sets. Environmental factors, such as obscuration (e.g. dust, rain, snow, etc.), lighting and crop stand attributes may also be used by error estimation system **162** in order to generate a georeferenced estimate of error corresponding to the yield estimate output by yield estimation system **160**.

Local material repository capacity **164** may be a value that is stored on harvesting machine **100**, itself. It is illustratively indicative of the overall capacity of the clean grain tank on machine **100**. It can also be a value that is stored at a remote location, and accessed by communication system **202** when harvesting machine **100** starts, or is about to start, its operation.

Position sensor **166** can be any of a wide variety of different types of position sensors such as a global positioning system (GPS) receiver, a dead reckoning system, or a wide variety of other systems that provide an indication of a current geographic location of harvesting machine **100**. They can provide orientation, ground speed and other information as well.

Current fill level sensor **170** illustratively senses a fill level in the local material repository (e.g., the clean grain

tank) on harvesting machine **100**. It can be any of a wide variety of different level sensors, such as an optical sensor, a weight or mass sensor, a mass flow sensor that measures the amount of material entering clean grain tank **132** since it was last emptied, etc.

Yield and corresponding error map generation logic **168** illustratively generates a georeferenced yield estimate, along with a georeferenced error estimate. This is illustratively a georeferenced predicted yield map for at least a portion of the field over which harvester **100** is traveling, along with an error estimate corresponding to the georeferenced predicted yield. In one example, the georeferenced yield and corresponding error map is generated with a resolution that corresponds to segments along a travel path of harvesting machine **100**. For instance, where harvesting machine **100** harvests 12 rows at a time, then the georeferenced yield and corresponding error map will illustratively output estimated yield and error values for geographic locations that are 12 rows wide and a certain row length (e.g., 10 meters in linear row length). Of course, these values are examples only and the width of the path of harvesting machine **100**, and the length of the segments for which a yield and corresponding error is estimated can vary widely. In one example, they can be controlled or varied based on user inputs or otherwise. The yield and corresponding error map are output by logic **168** to path processing system **174**.

Remaining capacity identifier logic **172** illustratively generates a value indicative of a remaining capacity in the local material repository (e.g., the clean grain tank **132**) on harvesting machine **100**. This value is illustratively updated as machine **100** continues to operate, performing the harvesting operation and filling its clean grain tank.

Possible path generator logic **184** identifies a number of different, possible geographic paths of harvesting machine **100** through the field over which it is harvesting. In doing so, it illustratively takes into account the width of the harvesting head on machine **100**, crop that has already been harvested, the geographic location of any other harvesters or machines in the field, etc. It correlates the possible paths to the georeferenced yield and corresponding error map generated by logic **168**. Therefore, it identifies geographic locations or routes, on that map, that correspond to different paths that harvester **100** can take.

As is described in greater detail below, rendezvous point identifier logic **185** can identify different rendezvous points where harvester **100** can meet one or more haulage units in the field. This can be based on the location and fill status (full, empty, unloading, waiting to unload, etc.) of the haulage units, the location of harvester **100**, the speed of the vehicles, the routes, field terrain, etc. Uncertainty estimator **187** generates an uncertainty level corresponding to each rendezvous point. The uncertainty level accounts for various uncertainties in identifying the rendezvous points.

Cumulative yield per path identifier logic **186** identifies the cumulative yield that harvester **100** will encounter, as it travels over the different paths identified by logic **184**. For instance, it may be that the possible paths output by logic **184** have corresponding estimated yields, in 10-meter segments along the path. Therefore, as harvester **100** travels along a given path, the yield it has encountered will accumulate, with each harvested segment. Therefore, cumulative yield per path identifier logic **186** identifies the cumulative yield that will be encountered by harvester **100**, as it travels along each of the possible paths output by logic **184**.

Georeferenced probability distribution generator logic **188** then generates a georeferenced probability distribution indicative of the probability that the local material repository

(e.g., the clean grain tank) will reach its capacity at different geographic locations along the field. It will do this for each path output by logic **184**, based upon the cumulative yield output by logic **186**.

Path surfacing interaction logic **190** then surfaces the various paths, along with the probability distributions, for user interaction. In one example, the user can select one of the paths and the machine **100** will be automatically controlled to follow that path. In another example, the operator can provide inputs to control machine **100** to travel along one of the paths. These and other operations can be performed, some of which are described in more detail below.

Measured yield identifier logic **192** measures the actual yield encountered by harvester **100**. This value can be fed back to yield estimation system **160**, or error estimation system **162** in order to correct the yield estimate, or the error estimate. These corrected values can then be used by logic **168** to generate an updated yield and corresponding error map.

Action threshold comparison logic **194** illustratively allows action thresholds to be set given the georeferenced probability distribution output by logic **188**. For instance, it may be that, if the probability that the clean grain tank is full exceeds a certain threshold, an alert may be generated using operator interface mechanisms **180** for operator **183**. Other action thresholds can be set and used to perform other operations as well, and some of them are described in more detail below.

Based on the various information generated by path processing system **174**, control signal generator **176** generates control signals that are applied to controllable subsystems **178**. For instance, control signal generator **176** can generate control signals to control propulsion subsystem **198** to control the speed of harvesting machine **100**. By way of example, if harvesting machine **100** is going to be full relatively quickly, but it will take a haulage unit a longer amount of time to reach it and unload it, then control signal generator **176** can control propulsion subsystem **198** to slow down harvesting machine **100**. This may reduce grain losses and it may increase the likelihood that the haulage unit will be able to travel to harvesting machine **100** before harvesting machine **100** has reached it capacity. In another example, if the georeferenced probability distribution indicates that, given the path harvesting machine **100** is taking, it will not be full before a haulage unit reaches it, then control signal generator **176** may generate control signals to control propulsion subsystem **198** to increase the speed of harvesting machine **100** so that it can harvest more crop, and be closer to its capacity, when a haulage unit reaches it. These are examples only.

Control signal generator **176** can also generate control signals to control steering subsystem **200**. For instance, it may be that operator **183** selects a possible path that is output by path processing system **174**. In that case, control signal generator **176** can control steering subsystem **200** to steer harvesting machine **100** along the selected path.

Control signal generator **176** can also control communication subsystem **202** to communicate various information within harvesting machine **100** or to one or more remote systems. The remote systems may be able to connect with communication subsystem **202** over a network, such as a cellular communication network, a wide area network, a local area network, a near field communication network, or a wide variety of other networks or combinations of networks.

Control signal generator **176** can also generate control signals to control operator interface logic **204**. The operator

interface logic **204** can control operator interface mechanisms **180**, and receive operator interactions through those mechanisms. Operator interface mechanisms **180** may include such things as a steering wheel, joystick, levers, pedals, linkages, buttons, switches, and other such mechanisms. It can also include such things as a touch sensitive display screen so that user input mechanisms can be displayed, and actuated by operator **183**, using touch gestures. Mechanisms **180** can include a microphone and corresponding speech recognition system, as well as a speaker and corresponding speech synthesis system. Operator interface mechanisms **180** can include a wide variety of other mechanical, electromechanical, visual, audio or haptic systems as well. Those mentioned are mentioned for the sake of example only.

FIGS. 3A and 3B show a flow diagram illustrating one example of the operation of harvesting machine **100** in generating action signals based upon a georeferenced probability distribution indicating a georeferenced probability of the local material repository (e.g., clean grain tank **132**) on machine **100** reaching its capacity. It is first assumed that harvesting machine **100** and the worksite location (e.g., the field to be harvested) are identified. This is indicated by block **220** in the flow diagram of FIG. 3. In one example, the information identifying the particular harvesting machine **100** also includes the local material repository capacity information **164**. It can include the geographic location of the field to be harvested, as indicated by block **222**, and it can include a wide variety of other things, as indicated by block **224**.

Yield and corresponding error map generation logic **168** then receives or obtains a predicted yield for at least one possible path of harvesting machine **100** at the worksite or field being harvested. This is indicated by block **226**. In one example, logic **168** outputs a georeferenced predicted yield map which identifies predicted yield at different geographical locations within the field. This is indicated by block **228**. It can be based on the yield estimate received from yield estimation system **160**.

Logic **168** can also output a georeferenced yield error estimate which identifies an estimate of error at the geographic locations within the field, for which the yield has been estimated. This can be based on the error estimate received from error estimation system **162**. Outputting the corresponding yield error estimate is indicated by block **230** in the flow diagram of FIG. 3.

The georeferenced yield and corresponding error map can be output for at least one path (or possible path) of harvesting machine **100** through the field or worksite where it is harvesting. This is indicated by block **232**. It will be appreciated that it can be output for multiple different paths as well, or in other ways. This is indicated by block **234**.

Remaining capacity identifier logic **172** also receives a current fill level of the local material repository (e.g. the grain tank). This is indicated by block **236** in the flow diagram of FIG. 3. This can be based on a sensor input **238** from current fill level sensor **170**, or it can be obtained in other ways, as indicated by block **240**. Remaining capacity identifier logic **172** then identifies the available capacity (or remaining capacity) in the local material repository (in the grain tank). This is indicated by block **238**. For instance, the current fill level (or measured amount) of material in the grain tank can be subtracted from the capacity of the repository to give the remaining capacity.

Possible path generator logic **184** identifies one or more different possibly paths of machine **100** through the field being harvested. It correlates those paths with the yield and

corresponding error map generated by logic **168**. Cumulative yield per path identifier logic **186** then identifies the cumulative yield, for different sections along each of the identified paths. The cumulative high yield (given the expected yield plus an amount corresponding to the identified error) and the cumulative low yield (given the expected yield minus an amount corresponding to the estimated error) can be generated for each path as well. Generating a georeferenced estimate of yield is indicated by block **244**. Identifying the yield for different field segments is indicated by block **246** and identifying the corresponding error is indicated by block **248**. Identifying cumulative expected yield across different segments along one or more different possible paths for machine **100** is indicated by block **250**. Identifying the cumulative high and low yield values across those segments, based upon the estimated error value, is indicated by block **252**. The georeferenced estimate of yield can be generated in a wide variety of other ways as well, and this is indicated by block **254**.

Table 1 illustrates one example of this in more detail.

TABLE 1

Line	Value	Seg 1	Seg 2	Seg 3	Seg 4	Seg 5
1	Estimated Yield (bu)	50.0	60.0	55.0	50.0	45.0
2	Estimated Yield Error	5%	8%	7%	8%	10%
3	-> Range High	52.5	64.8	58.8	54.0	49.5
4	-> Range Low	47.5	55.2	51.2	46.0	40.5
5	Cumulative High	52.5	117.3	175.8	229.8	279.3
6	Cumulative Mean	50.0	110.0	165.0	215.0	260
7	Cumulative Low	47.5	102.7	153.9	199.9	240.4
8	Capacity Risk Level	LOW	LOW	MED	HIGH	HIGH

Table 1 shows one example of information that can be generated in determining a georeferenced probability distribution indicative of where the grain tank **132** in machine **100** might reach its capacity. Table 1 shows the information for a single path of machine **100** that has been broken into five geographic segments along the path (e.g., along the field being harvester). The segments are identified as Seg1-Seg5 in Table 1 above.

Line 1 in Table 1 shows a value (in bushels) of the estimated or expected yield for each of the segments. This is illustratively the yield received from yield estimation system **160** and mapped to the different geographic locations by the yield and corresponding error map generator logic **168**. Line 2 in Table 1 shows the estimated error corresponding to each yield value. In the example shown in Table 1, the estimated yield error is the estimated $3-\Sigma$ error for a normal distribution. Lines 3 and 4 in Table 1 show the estimated high and low yield levels for each segment. For instance, line 3 shows a high yield value which includes the estimated yield from line 1 increased by the estimated error in line 2. Line 4 shows a value that is equal to the estimated yield in line 1 decreased by the estimated yield error.

Lines 5, 6 and 7 in Table 1 show the cumulative yield (in bushels) and specifically the cumulative high yield, the cumulative mean yield and the cumulative low yield, respectively. Thus, the cumulative high yield shown in line 5, for segment 2, is the sum of the high yield values from line 3, for segments 1 and 2. The cumulative value in line 5 for segment 3 is the sum of the values for segments 1, 2 and 3 from line 3.

Line 8 in Table 1 is an indicator that indicates the probability of the clean grain tank **132** on harvesting machine **100** reaching its capacity in each of the segments 1-5 shown in Table 1. The probabilities are divided into

ranges identified by the values low, medium and high. For the sake of the example shown in Table 1, the probability that the grain tank of harvesting machine **100** will reach its capacity in any given segment is low if the available capacity for the grain tank on harvesting machine **100** is greater than the cumulative high value corresponding to that segment. For instance, in segment 1, it is assumed that the local material repository (e.g., the clean grain tank **132**) has a capacity of 300 bushels, and the current level in the grain tank is 130 bushels. The available capacity is thus 170 bushels. Therefore, the probability that the clean grain tank for machine **100** will reach its capacity in segment 1 is low because the available capacity of 170 bushels is greater than the cumulative high value of 52.5 bushels. The probability is the same in segment 2 because the available capacity of 170 bushels is still greater than the cumulative high of 117.3 bushels. However, in segment 3, it can be seen that the probability of the clean grain tank for harvesting machine **100** reaching its capacity is medium. This is because the cumulative mean shown in line 6 of Table 1 is less than the available capacity of 170 bushels, but the available capacity of 170 bushels is less than the cumulative high of 175.8 bushels shown for segment 3, in line 5 of Table 1.

The high probability range is defined by the available capacity being less than the cumulative mean. Therefore, segments 4 and 5 of the path represented by the information in Table 1 are assigned a high probability value because the available capacity of 170 bushels is less than the cumulative mean of 215 bushels and 260 bushels in segments 4 and 5, respectively. These representations of low, medium and high probability are examples only. Others can be used.

Generator logic **188** generates the georeferenced probability distribution of the local material repository becoming full, as shown in line 8 of Table 1, for example. For instance, it generates a probability distribution identifying different probabilities, at different geographic locations, where those probabilities are indicative of the probability that the grain tank on machine **100** will be full, at that particular geographic location. This is indicated by block **256** in the flow diagram of FIG. **3**. The probabilities can be raw numeric probabilities, or they can be divided into categories or thresholds (again, as shown in line 8 of Table 1). For instance, a low probability may be indicative of a geographic location where the available capacity in the grain tank of machine **100** is greater than the cumulative high yield (the estimated yield plus an amount indicated by the expected error). Setting a low threshold to this value is indicated by block **258** in the flow diagram of FIG. **3**.

A medium probability level may be indicated when the cumulative mean (e.g., that shown in line 6 of Table 1) is less than the available capacity, which is, itself, less than the cumulative high (the value shown in line 5 in Table 1). Defining a medium probability level in this way is indicated by block **260** in the flow diagram of FIG. **3**.

A high probability level may be defined where the available capacity of the grain tank in machine **100** is less than the cumulative mean shown in line 6 of Table 1 above. Defining the high probability category in this way is indicated by block **262**. The georeferenced probability distribution can be identified in other ways as well. This is indicated by block **264**.

Path surfacing/interaction logic **190** then illustratively correlates the georeferenced probability distribution to a current position of the harvesting machine. This is indicated by block **266** in the flow diagram of FIG. **3**. The current geographic location of machine **100** can be obtained from position sensor **166**, or otherwise. Path surfacing/interaction

logic **190** can receive other information as well, such as possible rendezvous points where hauling units may rendezvous with machine **100**, to unload it. This is indicated by block **268** in the flow diagram of FIG. **3**, and it is described in greater detail below with respect to FIGS. **4** and **4A**. The georeferenced probability distribution can be correlated to the current position of machine **100** in other ways as well, and this is indicated by block **269**.

FIG. **3C** is one example of a user interface display **270** that can be used to surface information such as that shown in Table 1. Display **270** shows the position of machine **100**, and its direction of travel, with an icon or other graphical representation **272**. It is making a current pass through the field. FIG. **3** shows that a portion of the field being harvested has been divided into segments. Each segment is in a current pass, or one of three different optional passes that the machine can take after it makes a turn in the headland area graphically represented by area **274**. Each cell on the display **270** represents a segment in the field. The letter in each cell represents the corresponding probability value, indicative of the probability that the clean grain tank **132** on machine **100** will be full, in that segment. Therefore, it can be seen in FIG. **3C** that the machine can finish its first pass and reach the headland area **274**, for a headland turn, without the probability that its grain tank **132** will reach its capacity exceeding the low level. Then, however, once the machine makes a headland turn, it can choose one of three different path options. It can be seen with the path option 1 that the machine can make a turn and continue harvesting all the way to segment **276** in the field represented by the display, before the probability that its grain tank will reach its capacity moves from the low probability level to the medium probability level. It can continue harvesting until it reaches segment **278** before that value moves to a high probability value.

However, if the machine takes path option 2, it can only harvest to segment **280** before the probability that its clean grain tank **132** will reach its capacity will switch from a low to a medium probability level. At segment **282**, the probability goes to a high probability level.

With path option 3, the machine can harvest until it reaches field segment **284** before the probability reaches a medium value. It can harvest until it reaches field segment **286** before the probability that its grain tank **132** will reach its capacity changes to a high probability value.

Returning again to the flow diagram shown in FIG. **3**, action threshold comparison logic **194** compares a current probability (or other value) to various action thresholds, some examples of which were described above as possibility values low, medium and high. When the value reaches an action threshold, then certain actions may be taken.

It will be noted that the action thresholds can be a wide variety of different thresholds, based upon a wide variety of different criteria. For instance, a threshold may be set that indicates a certain distance that the machine **100** is from a field segment where the probability value will change values. For instance, and again referring to FIG. **3C**, assume that an action threshold has been set to indicate when the machine is less than five segments away from a field segment where the probability value changes. By way of example, assume that the distance threshold is set to five segments. Assume further that the operator of the machine takes a headland turn and begins to harvest along path option 1 in FIG. **3C**. Then, when the harvester reaches the field segment **290**, action threshold comparison logic **194** may be

triggered to take some action, because the machine is now within 5 field segments of its probability value changing from low to medium.

The thresholds can take a wide variety of other forms as well. For instance, the threshold may be set to a value corresponding to a point where the probability value actually does change. That threshold would be met, for example, when machine **100** moves from a field segment corresponding to probability value of low to an adjacent field segment corresponding to a probability value of medium or, where it moves from a field segment corresponding to a probability value of medium to an adjacent field segment where the corresponding probability value is high. The threshold can be set to identify a certain distance from a headland turn (so that the operator has adequate opportunity to select his or her next pass through the field), or it can be set based on time, such as a certain time before the probability that its grain tank is full moves to a next highest probability value. The threshold can be set in a wide variety of other ways as well. Determining whether an action threshold has been reached is indicated by block **292** in the flow diagram of FIG. **3**.

When an action threshold has been reached, action threshold comparison logic **194** indicates this to control signal generator **176**. Control signal generator **176** then generates one or more control signals to control one or more controllable subsystems **178** based upon the particular action threshold that has been reached. Generating control signals under these circumstances is indicated by block **294** in the flow diagram of FIG. **3**.

Control signal generator **176** can generate control signals in a wide variety of different ways. For instance, it can generate different control signals based upon a variety of different action thresholds and desired responses. This is indicated by block **296**. By way of example, if the harvesting machine **100** has entered a segment where the probability that its grain tank will reach its capacity is high, then control signal generator **176** may generate a control signal to control operator interface logic **204** to sound an alarm or to otherwise generate an alarm output for operator **183**. Or, under those circumstances, control signal generator **176** may generate a control signal to control propulsion subsystem **198** to stop harvesting machine **100** so that the grain tank does not overflow, or to wait for a haulage unit, or to wait until operator **183** overrides that command. However, if the machine **100** has entered a segment where the probability has raised from low to medium, then a display may be generated, but without an alarm. Similarly, if harvester **100** is in a segment where the probability is low, then control signal generator **176** may control the controllable subsystems **178** so that a simple display is generated, or so that no display is generated.

Control signal generator **176** may control steering subsystem **200** to steer machine **100** based upon the action threshold that was crossed. For instance, if a haulage unit is currently available, or will soon be available, to unload machine **100**, then control signal generator **176** may generate steering control signals to control steering subsystem **200** so that the machine **100** takes machine path 2 shown in FIG. **3C**. However, if a haulage unit is not presently available, and may not be available for some time, then control signal generator **176** may generate control signals to control steering subsystem **200** to take path option 1 shown in FIG. **3C**. This will delay the time when the clean grain tank on machine **100** will likely be full. This will give the haulage unit time to reach machine **100**. Controlling the steering actuator, or steering subsystem **200** is indicated by block **298** in the flow diagram of FIG. **3**.

Where the action threshold indicates a distance or time from a position where the probability value will increase, then control signal generator **176** may control propulsion subsystem **198** to decrease the speed, or to increase the speed of machine **100**. For instance, if the estimated yield values for a certain portion of the field have fallen, this may indicate that machine **100** can increase its speed, because the next field segment where the probability that its grain tank will be full increases is a relatively large distance from its current location. Similarly, if the yield has increased, then control signal generator **176** may generate control signals to control propulsion subsystem **198** to reduce the speed of machine **100**, so that the time before its grain tank is likely going to be at its capacity is increased. This may be done in order to give a haulage unit extra time to reach machine **100** so that machine **100** can continue harvesting, without stopping and remaining idle to wait for a haulage unit. Controlling the speed actuator or propulsion subsystem is indicated by block **300** in the flow diagram of FIG. **3**.

Control signal generator **176** can control operator interface logic **204** to control various operator interface mechanisms **180**. As discussed above, this can include generating a display (such as that shown in FIG. **3C**), generating an alarm, generating audible, visual, or haptic outputs, as well as receiving operator inputs through operator interface mechanisms **180**. Generating control signals to control operator interface logic **204** and operator interface mechanisms **180** is indicated by block **302** in the flow diagram of FIG. **3**.

Control signal generator **176** can also generate control signals to control communication subsystem **202**. This is indicated by block **304** in the flow diagram of FIG. **3**. For instance, it may be that machine **100** has crossed the threshold to indicate that it is now in a field segment where it is highly probable that its grain tank will reach capacity. In that case, control signal generator **176** can automatically generate control signals to control communication subsystem **202** to send a message to a haulage unit (such as the driver of a tractor pulling one or more grain carts) that machine **100** is about to have a full grain tank. It can control communication subsystem **202** to communicate with a site manager or farm manager or with a semi-driver, or with other remote machines and people as well.

Control signal generator **176** can also illustratively generate control signals that are communicated using communication subsystem **202** to communicate with or control other machines. For instance, the control signals may generate a display or other alert in the operator compartment of a haulage unit indicating that the harvester needs haulage attention. It can provide a most direct route (or an otherwise preferred route) from the haulage unit's current location to the location of machine **100**. It can automatically control the haulage unit to follow that route. By automatic it is meant that the operation or function can be carried out without further operator involvement except, perhaps, to authorize or initiate the function. Controlling and communicating with other machines is indicated by block **306** in the flow diagram of FIG. **3**. Control signal generator **176** can generate a wide variety of other control signals, based upon the action threshold that has been reached. This is indicated by block **308**.

In one example, this type of operation continues on machine **100** until the harvesting operation is complete, as indicated by block **310**. If the harvesting operation is not complete, then the harvester may wait for a pre-determined time period, or may travel a specified distance, or may wait for other criteria to occur, and then return to processing at

block 226, where information is received or obtained in order to update the georeferenced probability distribution map. This is indicated by block 312.

FIG. 4 is a flow diagram showing one example of the operation of machine 100 and path processing system 174 in not only identifying a plurality of different possible paths of machine 100 through a field, and the corresponding georeferenced probability distribution, but also identifying potential rendezvous points where a haulage unit (such as a tractor pulling one or more grain carts) may rendezvous with machine 100 to unload it. Control signal generator 176 first controls communication subsystem 202 to identify the locations of any support vehicles that are supporting harvester 100 in the field being harvested. This is indicated by block 314 in the flow diagram of FIG. 4. It can identify the positions, for instance, of various different haulage units (tractor/grain cart combinations). This is indicated by block 316. It can identify the location of a semi or other transport truck as indicated by block 318, and it can identify the locations of any of a wide variety of other vehicles. This is indicated by block 320.

FIG. 4A shows one example of a user interface display 322 indicating some of these items. User interface display 322 has some items that are similar to the user interface display 270, shown in FIG. 3C, and similar items are similarly numbered. However, it can be seen in FIG. 4A that display 322 also shows a position of a semi-truck 324, a first haulage unit or haulage vehicle 326 and the position of a second haulage unit or haulage vehicle 328. In one example, the locations of vehicles 324-328 are shown relative to the icon 272 representing harvester 100. Also, the graphical illustrations of vehicles 326 and 328 may indicate their status (such as whether they are full, or empty). By way of example, the lowercase letters identified on haulage vehicle 326 (“hv1”) may indicate that it is empty. The uppercase letters on haulage vehicle (“HV2”) may indicate that it is full. The fill statuses can be indicated in a wide variety of other ways as well.

Control signal generator 176 may control communication subsystem 202 to receive or obtain other information, such as timing and other parameter information from the various vehicles. This is indicated by block 330 in the flow diagram of FIG. 4. For instance, it may receive an indication from vehicles 326 and/or 328 indicating an unload time, which identifies a time that will be needed for the vehicle to unload its grain into semi 324 or elsewhere (which may be based on historic values or an estimate, knowing the size of the cart, the characteristics of the unloading mechanism, etc.). This is indicated by block 332. It may receive information indicative of the travel speed of vehicles 326 and 328, which may indicate how long it will take those vehicles to reach semi 324 and to return to the various locations on the field being harvested by harvester 100. Receiving an indication of the travel speed is indicated by block 334 in FIG. 4. The communication subsystem 202 may be controlled to receive information indicative of the fuel consumption of haulage units or vehicles 326 and 328. This may be the rate of fuel consumption, estimated fuel consumption to reach a location (such as to travel to semi 324 and back to various locations) on the field being harvested by harvester 100, or other information. Receiving fuel consumption parameters is indicated by block 336 in the flow diagram of FIG. 4. Communication subsystem 202 can receive a wide variety of other timing information or parameters as well. This is indicated by block 338.

Rendezvous point identifier logic 185 identifies likely rendezvous points for vehicles 326 and 328 with harvester

100. This is indicated by block 340 in the flow diagram of FIG. 4. The likely rendezvous points are determined based upon the location of the vehicles and the various timing and parameter information received at block 330. By way of example, in the user interface display illustrated in FIG. 4A, the “1” indicates where haulage vehicle hv1 (326) will be able to meet harvester 100 in the corresponding path. For instance, if harvester 100 makes a headland turn in headland area 274 and chooses to harvest along path option 1, the haulage vehicle 1 (326) can rendezvous with harvester 100 in field segment 342. This means that rendezvous point identifier logic 185 has calculated that haulage vehicle hv1 (326) can finish unloading at semi 324, travel to the headland area 274 in the left of the field being harvested, and then catch up to harvesting machine 100 (as it is traveling left to right along path option 1 in the field) at field segment 344. Similarly, if machine 100 chooses path option 2, then haulage vehicle 1 (326) will catch up to it at field segment 344. If harvester 100 begins harvesting in path option 3, then haulage vehicle 1 (326) will catch up to it at field segment 346.

By contrast, haulage vehicle 2 (328) needs to travel all the way back to semi 324, and unload before it is available to travel back to the harvester 100. Therefore, it is not able to rendezvous with harvester 100 until harvester 100 reaches field segment 348 (in path option 1), field segment 350 (in path option 2) and field segment 352 (in path option 3).

Uncertainty estimator 187 may identify rendezvous points 342-352 with an estimated uncertainty level. The uncertainty may be influenced by the topography of the field, by the certainty with which logic 185 knows the estimated speed at which the vehicle will be traveling, the weather, the soil conditions, among other things. Therefore, it may be that display 322 displays the rendezvous points (e.g., the “1” and “2”) in varying colors indicative of how certain the rendezvous points are to be correct. For instance, if they are displayed in red, this may indicate a lowest probability that the rendezvous point is correct (or lowest confidence) whereas if they are displayed in green, this may indicate a highest probability that the rendezvous points are correct (or highest confidence).

Once the rendezvous points are identified, then control signal generator 176 illustratively generates control signals based upon the likely rendezvous points. This is indicated by block 354 in the flow diagram of FIG. 4. By way of example, control signal generator 176 can generate control signals to perform automatic selection of a particular path option, and control machine 100 to move along that path option. This is indicated by block 356. For instance, it may be that control signal generator 176 generates control signals to control propulsion subsystem 198 and steering subsystem 200 to control machine 100 to travel along path option 3, because it is most likely that haulage vehicle 1 (326) will be able to receive grain from machine 100 before it is full. In another example, however, it may be that control signal generator 176 controls propulsion subsystem 198 and steering subsystem 200 to control machine 100 to take path option 1 because that is the path that allows machine 100 to get as full as possible before the haulage vehicle arrives. Control signal generator 176 can control propulsion subsystem 198 and steering subsystem 200 to cause combine 100 to select a next pass after reaching headland area 274 based on different criteria. In one example, it may select the next pass as the one with the earliest fill point (e.g., where the georeferenced probability distribution indicates that the combine will likely reach its fill capacity earliest in the pass). In another example, it may choose the pass with the latest fill point. It

may choose the pass that has a best rendezvous with a moving haulage vehicle (e.g., where the haulage vehicle is most likely to reach harvester **100** before its grain tank is full). It may also choose a pass where the most likely fill point is closest to a fixed haulage vehicle (e.g., where it is closest to a truck parked in the headlands area **274** or elsewhere). These and other examples as well as other criteria are contemplated herein.

In another example, control signal generator **176** can control operator interface logic **204** to surface the path options and corresponding rendezvous points on an operator interface mechanism **180** for interaction by operator **183**. As is shown in the example illustrated in FIG. **4A**, each of the path options 1-3 may be actuatable so that operator **183** can select one of the path options by simply tapping on that actuator. If the user taps on the actuator, then control signal generator **176** detects this and generates control signals to again control the propulsion subsystem **198** and steering subsystem **200** to control machine **100** to travel down the selected path option. Surfacing the options on an operator interface is indicated by block **358** in the flow diagram of FIG. **4**, and detecting operator selection of one of the options is indicated by block **360**. Automatically controlling the vehicle based upon the selected path option is indicated by block **362**. The path option can be selected in other ways as well, such as using a voice command, a point and click device, or in other ways.

It will also be noted that, in one example, control signal generator **176** can generate control signals to control communication subsystem **202** to communicate the rendezvous points to other vehicles. This is indicated by block **364** in the flow diagram of FIG. **4**. By way of example, it may be that communication subsystem **202** is controlled to communicate the geographic location of a desired rendezvous point to haulage vehicle **1** (**326**) so that its operator can move to that rendezvous point as quickly as possible. It may be that the rendezvous point can be communicated to the navigation system in the haulage vehicle so that it automatically proceeds to the rendezvous point on the path option selected by the operator **183** or harvester **100**.

Control signal generator **176** can generate control signals to controllable subsystems **178** in a wide variety of other ways as well. This is indicated by block **366**.

FIG. **5** illustrates one example of path processing system **174**. Path processing system **174** includes an obstacle avoidance system **400** that illustratively includes obstacle detection logic **402**, obstacle boundary generation logic **404**, obstacle avoidance logic **406**, and unload path determination logic **408**. System **400** can include other items **409** as well. Path processing system **174** is also illustrated as having one or more processors **410**.

Operation of obstacle avoidance system **400** is discussed in further detail below. Briefly, system **400** is configured to identify obstacles in a field that are likely to hinder operation of harvester machine **100** during a harvesting operation and/or during unloading of machine **100** into a haulage unit or vehicle. System **400** is configured to generate obstacle boundaries corresponding to such obstacles, and to perform obstacle avoidance by controlling machine **100** and/or the haulage units to avoid the obstacles during their operation. In one example, the rendezvous point for the haulage unit and machine **100** is selected based on a determined fill probability of machine **100** (e.g., the georeferenced probability distribution) and the obstacle boundaries. Alternatively, or in addition, a corresponding unloading path to be

used by machine **100** and a haulage unit while machine **100** is being unloaded “on-the-go” is determined based on the obstacle boundaries.

Obstacle detection logic **402** is configured to detect obstacles in a field under consideration (e.g., a field on which machine **100** is performing a harvesting operation). Examples include, but are not limited to, obstacles related to terrain topology, terrain (e.g., soil) condition, and non-terrain obstacles. For instance, terrain topology-related obstacles include areas of terrain having a slope above a threshold, the edge or boundary of the field (e.g., a fence line, roadway, etc.), to name a few. Examples of terrain condition-related obstacles include indications of soil type or condition (e.g., saturated soil or areas of terrain that are under water), to name a few. Non-terrain obstacles can include obstructions such as poles or power lines on or along the field.

FIG. **6** illustrates one example of a method **412** of operating an agricultural harvesting machine. For sake of illustration, but not by limitation, method **412** will be described in the context of path processing system **174** shown in FIG. **5**.

At block **414**, the method determines the fill capacity of a harvested crop repository. One example is described above with respect to block **220** in FIG. **3A** in which the capacity of the grain tank on the harvester is determined based on identification of the harvesting machine. The determined fill capacity can be the maximum fill capacity of the machine, or a percentage thereof.

At block **416**, a predicted crop yield at a plurality of different field segments is obtained. In one example, block **416** is similar to block **226** discussed above with respect to FIG. **3A**.

In one example, the predicted crop yield obtained at block **416** is based on a priori data, and is used to generate a predictive map. The a priori data can be obtained in a variety of ways, such as from optical images of the field, forward of the harvester in the direction of travel. This can be obtained from on-board cameras or other imaging components on the harvester itself. Alternatively, or in addition, it can be obtained from aerial images, such as images obtained from unmanned aerial vehicles (UAVs) and/or satellite imagery.

Alternatively, or in addition, the predicted crop yield obtained at block **416** can be based on historical yield data for the field segments. For instance, yield data from a prior year’s harvest can be utilized to predict the crop yield in those field segments. This historical yield data can be stored on machine **100**, obtained from a remote system, or otherwise obtained by path processing system **174**. Further, it can be combined with the a priori data obtained from images of the field.

At block **418**, the crop is processed into the harvested crop repository. At block **420**, field data corresponding to one or more of the field segments is obtained. Illustratively, this includes obtaining actual yield data at block **422**. That is, as machine **100** is performing the harvesting operation, sensors on the harvester generate in situ data (or field data) indicative of the various sensed variables, during the operation. Here, the in situ data is actual yield data generated from yield sensors. In one example, yield sensors include on-board mass flow sensors that sense the mass of flow of grain (or other crop) entering the clean grain tank on machine **100**. That mass flow can then be correlated to a geographic position in the field from which it was harvested, to obtain an actual yield value for that geographic position (e.g., the field segment). Of course, the field data can be obtained at block **420** in other ways as well.

At block **424**, a yield correction factor is generated based on the predicted crop yield obtained at block **416** and the field data obtained at block **420**. Illustratively, the yield correction factor represents an error between the predicted crop yield (i.e., generated from previously collected data from a prior year's harvest, earlier or real-time collected image data from a satellites or drone, and/or other a priori data) and the actual yield data collected from on-board sensor. For example, the yield correction factor is calculated based on a difference between the predicted crop yield and the actual crop yield. This is represented by block **426**. Further, a yield correction factor can be generated individually for each field segment, and then the individual yield correction factors averaged, or otherwise combined, to obtain an overall yield correction factor.

At block **428**, the current fill level of the harvested crop repository is determined. One example is discussed above with respect to block **236** in FIG. 3A. For instance, a sensor input is received from a current fill level sensor **170**, or it can be obtained in other ways. In one example, the available capacity (or remaining capacity) in the repository is determined by remaining capacity identifier logic **172**.

At block **430**, a geo-referenced probability metric indicative of a probability of the repository becoming full is generated. In the illustrated example, this includes applying the yield correction factor, generated at block **424**, to the predicted yield, to obtain a corrected, predicted crop yield. This is represented by block **432**.

In one example, the corrected, predicted crop yield is identified for a plurality of different field segments in a path of the harvester. The corrected, predicted crop yield is determined by correcting the predicted crop yield for a field segment (obtained at block **416**) with the yield correction factor (generated at block **424**). Then, a cumulative expected yield across a field segment, or set of segments, in a path of the harvester is determined. One example of generating a geo-referenced probability distribution, and correlating such a distribution to a position of the machine, is discussed above with respect to blocks **256** and **266**.

The harvesting machine **100** and/or other support machines (such as haulage vehicles) can be controlled based on the probability metric. One example of generating control signals is discussed above with respect to block **294**.

In one example, operator interface mechanisms **180** are controlled to render an indication of the current fill level of the harvested crop repository, a remaining capacity of the repository, and/or a predicted time (and/or distance) until the repository is full and requires unloading. For instance, a countdown timer can be rendered to operator **183** and/or to other users. For instance, communication subsystem **202** can be controlled to communicate with a user associated with a haulage vehicle, to provide an indication of the fill level, remaining fill capacity, predicted time to fill capacity, and/or rendezvous path or point information. In another example, a haulage vehicle can be automatically controlled for the unloading operation.

In the illustrated example, at block **434**, obstacle detection and avoidance is performed during an unloading operation in which the harvested crop repository of machine **100** is unloaded into a haulage vehicle or other support machine.

FIG. 7 illustrates one example of a method **440** for performing obstacle detection and avoidance. For sake of illustration, but not by limitation, method **440** will be described in the context of obstacle avoidance system **400** shown in FIG. 5.

At block **442**, field data is received. This can include terrain topology information (represented by block **444**),

terrain conditions (represented by block **446**), and can include other data (represented by block **448**). In one example, terrain topology information represents topology characteristics, such as slope information, field boundaries, non-crop acres, trees, etc. The terrain topology information can be obtained from terrain maps retrieved from a local data store, a remote system, or otherwise.

Examples of terrain conditions include, but are not limited to, soil characteristics and conditions. This can include soil moisture information indicative of standing water, muddy soil, or other conditions that may adversely impact machine traversal or other operation across an area of terrain. This can be obtained in any of a variety of ways such as, but not limited to, soil moisture sensors.

At block **450**, a set of obstacles are identified based on the received field data at block **442**. In one example, this includes comparing the field data to threshold obstacle criteria. In one example, this can include threshold terrain slope, threshold soil moisture, threshold soil type, to name a few.

At block **452**, obstacle boundaries are generated based on the obstacles identified at block **450**. This can include generating a field map with the obstacle boundaries at block **454**. Illustratively, the obstacle boundaries identify areas of the field to be avoided during the unloading operation to unload the harvested crop repository of machine **100** to a haulage vehicle.

Additionally, the predicted and/or actual crop yield data can be utilized in generating the obstacle boundaries and path of harvester **100** during the harvesting operation and unloading into a haulage vehicle. For example, a predicted weight of harvester **100** at the different field segments can be determined based on the predicted crop yield data. Then, the predicted weight of harvester **100** can be utilized in conjunction with the terrain conditions (e.g., soil moisture, terrain slope, etc.) to identify areas to be avoided for any of a variety of reasons, such as, but not limited to, preventing the creation of ruts or ground compaction, preventing machine **100** from becoming stuck, etc. Similarly, the weight of a haulage vehicle before, during, and/or after unloading of harvester **100** can be determined and utilized to identify the obstacle boundaries.

Based on the obstacle boundaries, a rendezvous point or path is determined for the unloading operation. This is represented by block **456**. This can include a stationary unloading operation in which machine **100** is stopped while the repository is unloaded into a haulage vehicle. This is represented by block **458**. In another example, the unloading operation can be performed "on-the-go". This is represented by block **460**. In one example, machine **100** continues to traverse across the field and perform further harvesting operations while the repository is unloaded into a haulage vehicle that is moved at a same speed alongside machine **100**. In this case, a rendezvous path is generated that defines a traversal path across the field that is based on a start point for the unloading operation and an expected time duration for unloading the harvested crop into the haulage vehicle. In either case, the rendezvous point for the stationary unloading operation at block **458** or the starting point of the "on-the-go" unloading operation at block **460** is determined at block **456** based on the probability metric indicative of the probability of the repository becoming full at various segments in the field and the obstacle boundaries generated at block **452**.

At block 462, a control signal is generated based on the rendezvous or path. This can be used to control machine 100 at block 464, control the haulage vehicle at block 466, or otherwise at block 468.

FIG. 8 illustrates one example of determining a rendezvous point and unloading path for a harvesting machine. As shown in FIG. 8, machine 100 is making a current pass through field 470. Path processing system 174 has identified probability levels, indicative of a probability of the harvested crop repository of machine 100 becoming full, at each of a plurality of field segments 472. A haulage vehicle 474 is configured to rendezvous with machine 100 and perform an “on-the-go” unloading operation.

Further, a set of obstacle boundaries have been identified based on obstacles identified on field 470. Field segments that reside within the obstacle boundaries are illustrated by cross hatching in FIG. 8. Illustratively, a set of field segments 476 reside within at least one of the obstacle boundaries. For example, but not by limitation, segments 476 may be determined to have (or are likely to have) standing water, muddy conditions, and/or a slope above a threshold, which may adversely affect the unloading operation to unload the harvested crop from machine 100 into haulage vehicle 474.

Based on the probability levels associated with the field segments, and an estimated duration for the unloading operation, path processing system 174 identifies field segment 478 as a rendezvous point for haulage vehicle 474. Accordingly, it is determined that the unloading operation can begin at field segment 478 and can continue along a portion of the path represented by arrow 480, and will complete before machine 100 and/or haulage vehicle 474 enter one of the obstacle boundaries. Therefore, the unloading operation can begin even though the repository is partially full (e.g., 75%, etc.), but results in the unloading operation avoiding traversal in, through, or around an obstacle.

While the present discussion has proceeded with respect to a harvester, it can be used with other machines that collect or distribute material as well. Where the machine distributes material, the description is similar except that instead of generating a georeferenced possibility distribution of where the material repository will be full, it will represent the probability distribution of where the material repository will be empty.

The present discussion has mentioned processors and servers. In one example, the processors and servers include computer processors with associated memory and timing circuitry, not separately shown. They are functional parts of the systems or devices to which they belong and are activated by, and facilitate the functionality of the other components or items in those systems.

It will be noted that the above discussion has described a variety of different systems, components and/or logic. It will be appreciated that such systems, components and/or logic can be comprised of hardware items (such as processors and associated memory, or other processing components, some of which are described below) that perform the functions associated with those systems, components and/or logic. In addition, the systems, components and/or logic can be comprised of software that is loaded into a memory and is subsequently executed by a processor or server, or other computing component, as described below. The systems, components and/or logic can also be comprised of different combinations of hardware, software, firmware, etc., some examples of which are described below. These are only some examples of different structures that can be used to

form the systems, components and/or logic described above. Other structures can be used as well.

Also, a number of user interface displays have been discussed. They can take a wide variety of different forms and can have a wide variety of different user actuatable input mechanisms disposed thereon. For instance, the user actuatable input mechanisms can be text boxes, check boxes, icons, links, drop-down menus, search boxes, etc. They can also be actuated in a wide variety of different ways. For instance, they can be actuated using a point and click device (such as a track ball or mouse). They can be actuated using hardware buttons, switches, a joystick or keyboard, thumb switches or thumb pads, etc. They can also be actuated using a virtual keyboard or other virtual actuators. In addition, where the screen on which they are displayed is a touch sensitive screen, they can be actuated using touch gestures. Also, where the device that displays them has speech recognition components, they can be actuated using speech commands.

A number of data stores have also been discussed. It will be noted they can each be broken into multiple data stores. All can be local to the systems accessing them, all can be remote, or some can be local while others are remote. All of these configurations are contemplated herein.

Also, the figures show a number of blocks with functionality ascribed to each block. It will be noted that fewer blocks can be used so the functionality is performed by fewer components. Also, more blocks can be used with the functionality distributed among more components.

FIG. 9 is a block diagram of harvester 100, shown in FIG. 2, except that it communicates with elements in a remote server architecture 500. In an example embodiment, remote server architecture 500 can provide computation, software, data access, and storage services that do not require end-user knowledge of the physical location or configuration of the system that delivers the services. In various embodiments, remote servers can deliver the services over a wide area network, such as the internet, using appropriate protocols. For instance, remote servers can deliver applications over a wide area network and they can be accessed through a web browser or any other computing component. Software or components shown in FIG. 2 as well as the corresponding data, can be stored on servers at a remote location. The computing resources in a remote server environment can be consolidated at a remote data center location or they can be dispersed. Remote server infrastructures can deliver services through shared data centers, even though they appear as a single point of access for the user. Thus, the components and functions described herein can be provided from a remote server at a remote location using a remote server architecture. Alternatively, they can be provided from a conventional server, or they can be installed on client devices directly, or in other ways.

In the example shown in FIG. 9, some items are similar to those shown in FIG. 2 and they are similarly numbered. FIG. 9 specifically shows that path processing system 174, yield estimation system 160 and error estimation system 162 can be located at a remote server location 502. Therefore, harvester 100 accesses those systems through remote server location 502.

FIG. 9 also depicts another example of a remote server architecture. FIG. 9 shows that it is also contemplated that some elements of FIG. 2 are disposed at remote server location 502 while others are not. By way of example, field estimation system 160 or other systems or logic can be disposed at a location separate from location 502, and accessed through the remote server at location 502. Regard-

less of where they are located, they can be accessed directly by harvester **100**, through a network (either a wide area network or a local area network), they can be hosted at a remote site by a service, or they can be provided as a service, or accessed by a connection service that resides in a remote location. Also, the data can be stored in substantially any location and intermittently accessed by, or forwarded to, interested parties. For instance, physical carriers can be used instead of, or in addition to, electromagnetic wave carriers. In such an embodiment, where cell coverage is poor or nonexistent, another mobile machine (such as a fuel truck) can have an automated information collection system. As the harvester comes close to the fuel truck for fueling, the system automatically collects the information from the harvester using any type of ad-hoc wireless connection. The collected information can then be forwarded to the main network as the fuel truck reaches a location where there is cellular coverage (or other wireless coverage). For instance, the fuel truck may enter a covered location when traveling to fuel other machines or when at a main fuel storage location. All of these architectures are contemplated herein. Further, the information can be stored on the harvester until the harvester enters a covered location. The harvester, itself, can then send the information to the main network.

It will also be noted that the elements of FIG. **2**, or portions of them, can be disposed on a wide variety of different devices. Some of those devices include servers, desktop computers, laptop computers, tablet computers, or other mobile devices, such as palm top computers, cell phones, smart phones, multimedia players, personal digital assistants, etc.

FIG. **10** is a simplified block diagram of one illustrative embodiment of a handheld or mobile computing device that can be used as a user's or client's hand held device **16**, in which the present system (or parts of it) can be deployed. For instance, a mobile device can be deployed in the operator compartment of harvester **100** for use in generating, processing, or displaying the yield estimation data, path processing data, and/or obstacle avoidance data. FIGS. **11-12** are examples of handheld or mobile devices.

FIG. **10** provides a general block diagram of the components of a client device **16** that can run some components shown in FIG. **2**, that interacts with them, or both. In the device **16**, a communications link **13** is provided that allows the handheld device to communicate with other computing devices and under some embodiments provides a channel for receiving information automatically, such as by scanning. Examples of communications link **13** include allowing communication through one or more communication protocols, such as wireless services used to provide cellular access to a network, as well as protocols that provide local wireless connections to networks.

In other examples, applications can be received on a removable Secure Digital (SD) card that is connected to an interface **15**. Interface **15** and communication links **13** communicate with a processor **17** (which can also embody processors from previous FIGS.) along a bus **19** that is also connected to memory **21** and input/output (I/O) components **23**, as well as clock **25** and location system **27**.

I/O components **23**, in one embodiment, are provided to facilitate input and output operations. I/O components **23** for various embodiments of the device **16** can include input components such as buttons, touch sensors, optical sensors, microphones, touch screens, proximity sensors, accelerometers, orientation sensors and output components such as a display device, a speaker, and or a printer port. Other I/O components **23** can be used as well.

Clock **25** illustratively comprises a real time clock component that outputs a time and date. It can also, illustratively, provide timing functions for processor **17**.

Location system **27** illustratively includes a component that outputs a current geographical location of device **16**. This can include, for instance, a global positioning system (GPS) receiver, a LORAN system, a dead reckoning system, a cellular triangulation system, or other positioning system. It can also include, for example, mapping software or navigation software that generates desired maps, navigation routes and other geographic functions.

Memory **21** stores operating system **29**, network settings **31**, applications **33**, application configuration settings **35**, data store **37**, communication drivers **39**, and communication configuration settings **41**. Memory **21** can include all types of tangible volatile and non-volatile computer-readable memory devices. It can also include computer storage media (described below). Memory **21** stores computer readable instructions that, when executed by processor **17**, cause the processor to perform computer-implemented steps or functions according to the instructions. Processor **17** can be activated by other components to facilitate their functionality as well.

FIG. **11** shows one example in which device **16** is a tablet computer **600**. In FIG. **11**, computer **600** is shown with user interface display screen **602**. Screen **602** can be a touch screen or a pen-enabled interface that receives inputs from a pen or stylus. It can also use an on-screen virtual keyboard. Of course, it might also be attached to a keyboard or other user input device through a suitable attachment mechanism, such as a wireless link or USB port, for instance. Computer **600** can also illustratively receive voice inputs as well.

FIG. **12** shows that the device can be a smart phone **71**. Smart phone **71** has a touch sensitive display **73** that displays icons or tiles or other user input mechanisms **75**. Mechanisms **75** can be used by a user to run applications, make calls, perform data transfer operations, etc. In general, smart phone **71** is built on a mobile operating system and offers more advanced computing capability and connectivity than a feature phone.

Note that other forms of the devices **16** are possible.

FIG. **13** is one example of a computing environment in which elements of FIG. **2**, or parts of it, (for example) can be deployed. With reference to FIG. **13**, an example system for implementing some embodiments includes a general-purpose computing device in the form of a computer **810**. Components of computer **810** may include, but are not limited to, a processing unit **820** (which can comprise processors from previous FIGS.), a system memory **830**, and a system bus **821** that couples various system components including the system memory to the processing unit **820**. The system bus **821** may be any of several types of bus structures including a memory bus or memory controller, a peripheral bus, and a local bus using any of a variety of bus architectures. Memory and programs described with respect to FIG. **2** can be deployed in corresponding portions of FIG. **13**.

Computer **810** typically includes a variety of computer readable media. Computer readable media can be any available media that can be accessed by computer **810** and includes both volatile and nonvolatile media, removable and non-removable media. By way of example, and not limitation, computer readable media may comprise computer storage media and communication media. Computer storage media is different from, and does not include, a modulated data signal or carrier wave. It includes hardware storage media including both volatile and nonvolatile, removable

and non-removable media implemented in any method or technology for storage of information such as computer readable instructions, data structures, program modules or other data. Computer storage media includes, but is not limited to, RAM, ROM, EEPROM, flash memory or other memory technology, CD-ROM, digital versatile disks (DVD) or other optical disk storage, magnetic cassettes, magnetic tape, magnetic disk storage or other magnetic storage devices, or any other medium which can be used to store the desired information and which can be accessed by computer 810. Communication media may embody computer readable instructions, data structures, program modules or other data in a transport mechanism and includes any information delivery media. The term “modulated data signal” means a signal that has one or more of its characteristics set or changed in such a manner as to encode information in the signal.

The system memory 830 includes computer storage media in the form of volatile and/or nonvolatile memory such as read only memory (ROM) 831 and random access memory (RAM) 832. A basic input/output system 833 (BIOS), containing the basic routines that help to transfer information between elements within computer 810, such as during start-up, is typically stored in ROM 831. RAM 832 typically contains data and/or program modules that are immediately accessible to and/or presently being operated on by processing unit 820. By way of example, and not limitation, FIG. 13 illustrates operating system 834, application programs 835, other program modules 836, and program data 837.

The computer 810 may also include other removable/non-removable volatile/nonvolatile computer storage media. By way of example only, FIG. 13 illustrates a hard disk drive 841 that reads from or writes to non-removable, nonvolatile magnetic media, an optical disk drive 855, and nonvolatile optical disk 856. The hard disk drive 841 is typically connected to the system bus 821 through a non-removable memory interface such as interface 840, and optical disk drive 855 are typically connected to the system bus 821 by a removable memory interface, such as interface 850.

Alternatively, or in addition, the functionality described herein can be performed, at least in part, by one or more hardware logic components. For example, and without limitation, illustrative types of hardware logic components that can be used include Field-programmable Gate Arrays (FPGAs), Application-specific Integrated Circuits (e.g., ASICs), Application-specific Standard Products (e.g., ASSPs), System-on-a-chip systems (SOCs), Complex Programmable Logic Devices (CPLDs), etc.

The drives and their associated computer storage media discussed above and illustrated in FIG. 13, provide storage of computer readable instructions, data structures, program modules and other data for the computer 810. In FIG. 13, for example, hard disk drive 841 is illustrated as storing operating system 844, application programs 845, other program modules 846, and program data 847. Note that these components can either be the same as or different from operating system 834, application programs 835, other program modules 836, and program data 837.

A user may enter commands and information into the computer 810 through input devices such as a keyboard 862, a microphone 863, and a pointing device 861, such as a mouse, trackball or touch pad. Other input devices (not shown) may include a joystick, game pad, satellite dish, scanner, or the like. These and other input devices are often connected to the processing unit 820 through a user input interface 860 that is coupled to the system bus, but may be connected by other interface and bus structures. A visual

display 891 or other type of display device is also connected to the system bus 821 via an interface, such as a video interface 890. In addition to the monitor, computers may also include other peripheral output devices such as speakers 897 and printer 896, which may be connected through an output peripheral interface 895.

The computer 810 is operated in a networked environment using logical connections (such as a local area network—LAN, or wide area network WAN) to one or more remote computers, such as a remote computer 880.

When used in a LAN networking environment, the computer 810 is connected to the LAN 871 through a network interface or adapter 870. When used in a WAN networking environment, the computer 810 typically includes a modem 872 or other means for establishing communications over the WAN 873, such as the Internet. In a networked environment, program modules may be stored in a remote memory storage device. FIG. 13 illustrates, for example, that remote application programs 885 can reside on remote computer 880.

It should also be noted that the different examples described herein can be combined in different ways. That is, parts of one or more examples can be combined with parts of one or more other examples. All of this is contemplated herein.

Example 1 is an agricultural harvesting machine comprising:

- a harvested crop repository having a fill capacity;
- a crop processing functionality configured to engage crop in a field, perform a crop processing operation on the crop, and move the processed crop to the harvested crop repository;
- a fill level sensor configured to generate a fill level signal indicative of a current fill level of the harvested crop repository;
- a path processing system configured to:
 - obtain a predicted crop yield at a plurality of different field segments along a harvester path on the field;
 - obtain field data corresponding to one or more of the field segments, the field data being generated based on sensor data from a sensor on the agricultural harvesting machine as the agricultural harvesting machine is performing the crop processing operation;
 - generate a yield correction factor based on the received field data and the predicted crop yield at the one or more field segments;
 - based on applying the yield correction factor to the predicted crop yield, generate a georeferenced probability metric indicative of a probability that the harvested crop repository will reach the fill capacity at a particular geographic location along the field; and
 - a control signal generator configured to generate a control signal to control the agricultural harvesting machine based on the georeferenced probability metric.

Example 2 is the agricultural harvesting machine of any or all previous examples, wherein the predicted crop yield is based on a priori geo-referenced vegetative index data.

Example 3 is the agricultural harvesting machine of any or all previous examples, wherein the a priori georeferenced vegetative index data is generated based on image data of the field segments.

Example 4 is the agricultural harvesting machine of any or all previous examples, wherein the predicted crop yield is based on historical data from a prior harvesting operation corresponding to the field segments.

Example 5 is the agricultural harvesting machine of any or all previous examples, wherein the sensor comprises a crop yield sensor and the field data comprises crop yield data.

Example 6 is the agricultural harvesting machine of any or all previous examples, wherein the path processing system is configured to:

identify a cumulative predicted crop yield at a plurality of different field segments along the harvester path; and

generate a georeferenced probability distribution, indicative of a probability that the harvested crop repository will reach the fill capacity in the different field segments.

Example 7 is the agricultural harvesting machine of any or all previous examples, and further comprising:

an operator interface mechanism, wherein the control signal generator is configured to generate the control signal to control the operator interface mechanism based on the georeferenced probability metric.

Example 8 is the agricultural harvesting machine of any or all previous examples, wherein the path processing system comprises:

rendezvous point identifier logic configured to identify a rendezvous point for the agricultural harvesting machine and a haulage vehicle, and wherein the control signal generator is configured to generate the control signal based on the rendezvous point.

Example 9 is the agricultural harvesting machine of any or all previous examples, and further comprising:

a communication system, wherein the control signal generator is configured to generate the control signal to control the communication system to communicate an indication of the rendezvous point to the haulage vehicle.

Example 10 is the agricultural harvesting machine of any or all previous examples, and further comprising:

obstacle boundary generation logic configured to generate an obstacle boundary corresponding to one or more obstacles associated with the field, wherein the rendezvous point is identified based on the obstacle boundary.

Example 11 is the agricultural harvesting machine of any or all previous examples, wherein the one or more obstacles are related to at least one of terrain topology or terrain condition.

Example 12 is the agricultural harvesting machine of any or all previous examples, and further comprising:

unload path determination logic configured to determine an unload path, for unloading the harvested crop repository into the haulage vehicle, based on the obstacle boundary.

Example 13 is the agricultural harvesting machine of any or all previous examples, wherein the unload path is based on a predicted unload time for unloading the harvested crop repository into the haulage vehicle.

Example 14 is a method of controlling an agricultural harvesting machine, the method comprising:

obtaining a predicted crop yield at a plurality of different field segments along a harvester path on a field;

processing crop from the field and moving the processed crop to a harvested crop repository having a fill capacity;

obtaining field data corresponding to one or more of the field segments, the field data being generated based on sensor data from a sensor on the agricultural harvesting machine as the agricultural harvesting machine is processing the crop;

generating a yield correction factor based on the received field data and the predicted crop yield at the one or more field segments;

generating a fill level signal indicative of the current fill level of the harvested crop repository;

based on applying the yield correction factor to the predicted crop yield, generating a georeferenced probability metric indicative of a probability that the harvested crop repository will reach the fill capacity at a particular geographic location along the field; and

generating a control signal to control the agricultural harvesting machine based on the georeferenced probability metric.

Example 15 is the method of any or all previous examples, wherein the predicted crop yield is based on one or more of:

a priori geo-referenced vegetative index data generated based on image data of the field segments, or

historical data from a prior harvesting operation corresponding to the field segments.

Example 16 is the method of any or all previous examples, wherein the sensor comprises a crop yield sensor and the field data comprises crop yield data.

Example 17 is the method of any or all previous examples, and further comprising:

identifying a cumulative predicted crop yield at a plurality of different field segments along the harvester path; and

generating a georeferenced probability distribution, indicative of a probability that the harvested crop repository will reach the fill capacity in the different field segments.

Example 18 is the method of any or all previous examples, and further comprising:

identifying a rendezvous point for the agricultural harvesting machine and a haulage vehicle; and

generating the control signal based on the rendezvous point

Example 19 is the method of any or all previous examples, and further comprising:

generating an obstacle boundary corresponding to one or more obstacles associated with the field; and

identifying the rendezvous point based on the obstacle boundary.

Example 20 is an agricultural harvesting machine comprising:

a harvested crop repository having a fill capacity;

a crop processing functionality configured to engage crop in a field, perform a crop processing operation on the crop, and move the processed crop to the harvested crop repository;

a fill level sensor configured to generate a fill level signal indicative of a current fill level of the harvested crop repository;

a path processing system configured to:

obtain a predicted crop yield at a plurality of different field segments along a harvester path on the field;

generate a georeferenced probability metric indicative of a probability that the harvested crop repository will reach the fill capacity at a particular geographic location along the field;

generate an obstacle boundary corresponding to one or more obstacles associated with the field; and

identify a rendezvous point for the agricultural harvesting machine and a haulage vehicle based on:

the georeferenced probability metric, and

the obstacle boundary;

a control signal generator configured to generate a control signal to control the agricultural harvesting machine based on the rendezvous point.

Although the subject matter has been described in language specific to structural features and/or methodological acts, it is to be understood that the subject matter defined in the appended claims is not necessarily limited to the specific

features or acts described above. Rather, the specific features and acts described above are disclosed as example forms of implementing the claims.

What is claimed is:

1. An agricultural harvesting machine comprising:
 - a harvested crop repository having a fill capacity;
 - a crop processing functionality configured to engage crop in a field, perform a crop processing operation on the crop, and move the processed crop to the harvested crop repository;
 - a fill level sensor configured to generate a fill level signal indicative of a current fill level of the harvested crop repository;
 - a path processing system configured to:
 - obtain a predicted crop yield at a plurality of different field segments along a harvester path on the field;
 - obtain field data corresponding to one or more of the field segments, the field data being generated based on sensor data from a sensor on the agricultural harvesting machine as the agricultural harvesting machine is performing the crop processing operation;
 - generate a yield correction factor based on the received field data and the predicted crop yield at the one or more field segments;
 - based on applying the yield correction factor to the predicted crop yield, generate a georeferenced probability metric indicative of a probability that the harvested crop repository will reach the fill capacity at a particular geographic location along the field; and
 - a control signal generator configured to generate a control signal to control the agricultural harvesting machine based on the georeferenced probability metric.
2. The agricultural harvesting machine of claim 1, wherein the predicted crop yield is based on a priori georeferenced vegetative index data.
3. The agricultural harvesting machine of claim 2, wherein the a priori georeferenced vegetative index data is generated based on image data of the field segments.
4. The agricultural harvesting machine of claim 2, wherein the predicted crop yield is based on historical data from a prior harvesting operation corresponding to the field segments.
5. The agricultural harvesting machine of claim 1, wherein the sensor comprises a crop yield sensor and the field data comprises crop yield data.
6. The agricultural harvesting machine of claim 1, wherein the path processing system is configured to:
 - identify a cumulative predicted crop yield at a plurality of different field segments along the harvester path; and
 - generate a georeferenced probability distribution, indicative of a probability that the harvested crop repository will reach the fill capacity in the different field segments.
7. The agricultural harvesting machine of claim 1, and further comprising:
 - an operator interface mechanism, wherein the control signal generator is configured to generate the control signal to control the operator interface mechanism based on the georeferenced probability metric.
8. The agricultural harvesting machine of claim 1, wherein the path processing system comprises:
 - rendezvous point identifier logic configured to identify a rendezvous point for the agricultural harvesting machine and a haulage vehicle, and wherein the control

signal generator is configured to generate the control signal based on the rendezvous point.

9. The agricultural harvesting machine of claim 8, and further comprising:
 - a communication system, wherein the control signal generator is configured to generate the control signal to control the communication system to communicate an indication of the rendezvous point to the haulage vehicle.
10. The agricultural harvesting machine of claim 8, and further comprising:
 - obstacle boundary generation logic configured to generate an obstacle boundary corresponding to one or more obstacles associated with the field, wherein the rendezvous point is identified based on the obstacle boundary.
11. The agricultural harvesting machine of claim 10, wherein the one or more obstacles are related to at least one of terrain topology or terrain condition.
12. The agricultural harvesting machine of claim 11, and further comprising:
 - unload path determination logic configured to determine an unload path, for unloading the harvested crop repository into the haulage vehicle, based on the obstacle boundary.
13. The agricultural harvesting machine of claim 11, wherein the unload path is based on a predicted unload time for unloading the harvested crop repository into the haulage vehicle.
14. A method of controlling an agricultural harvesting machine, the method comprising:
 - obtaining a predicted crop yield at a plurality of different field segments along a harvester path on a field;
 - processing crop from the field and moving the processed crop to a harvested crop repository having a fill capacity;
 - obtaining field data corresponding to one or more of the field segments, the field data being generated based on sensor data from a sensor on the agricultural harvesting machine as the agricultural harvesting machine is processing the crop;
 - generating a yield correction factor based on the received field data and the predicted crop yield at the one or more field segments;
 - generating a fill level signal indicative of the current fill level of the harvested crop repository;
 - based on applying the yield correction factor to the predicted crop yield, generating a georeferenced probability metric indicative of a probability that the harvested crop repository will reach the fill capacity at a particular geographic location along the field; and
 - generating a control signal to control the agricultural harvesting machine based on the georeferenced probability metric.
15. The method of claim 14, wherein the predicted crop yield is based on one or more of:
 - a priori geo-referenced vegetative index data generated based on image data of the field segments, or
 - historical data from a prior harvesting operation corresponding to the field segments.
16. The method of claim 15, wherein the sensor comprises a crop yield sensor and the field data comprises crop yield data.
17. The method of claim 15, and further comprising:
 - identifying a cumulative predicted crop yield at a plurality of different field segments along the harvester path; and

31

generating a georeferenced probability distribution, indicative of a probability that the harvested crop repository will reach the fill capacity in the different field segments.

18. The method of claim **17**, and further comprising: 5
 identifying a rendezvous point for the agricultural harvesting machine and a haulage vehicle; and
 generating the control signal based on the rendezvous point.

19. The method of claim **18**, and further comprising: 10
 generating an obstacle boundary corresponding to one or more obstacles associated with the field; and
 identifying the rendezvous point based on the obstacle boundary.

20. An agricultural harvesting machine comprising: 15
 a harvested crop repository having a fill capacity;
 a crop processing functionality configured to engage crop in a field, perform a crop processing operation on the crop, and move the processed crop to the harvested crop repository;

32

a fill level sensor configured to generate a fill level signal indicative of a current fill level of the harvested crop repository;

a path processing system configured to:

obtain a predicted crop yield at a plurality of different field segments along a harvester path on the field;
 generate a georeferenced probability metric indicative of a probability that the harvested crop repository will reach the fill capacity at a particular geographic location along the field;

generate an obstacle boundary corresponding to one or more obstacles associated with the field; and

identify a rendezvous point for the agricultural harvesting machine and a haulage vehicle based on:

the georeferenced probability metric, and
 the obstacle boundary;

a control signal generator configured to generate a control signal to control the agricultural harvesting machine based on the rendezvous point.

* * * * *